# Benchmarking mortgage systematic risk and impact on pricing

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## Abstract

This study unifies the two dominant concepts of systematic credit risk: Beta for observed systematic risk and asset correlation (AC) for unobserved (frailty) systematic risk. An analysis for U.S. mortgages shows that Beta contributes up to 76% of the total systematic risk, and the remaining is accounted for by AC. The systematic risk levels vary across types of lenders, types of recourse laws, and states. In addition, we find a stronger sensitivity of mortgage rates to the exposures to the estimated systematic risk levels than the single regulatory value (15%). Our comprehensive findings on systematic risk components help banks develop more accurate models, enhance their risk management ability and achieve a better pricing scheme.

**Keywords**: Systematic Risk • Asset Correlation • Failure Beta • Mortgage • Payoff Risk • Default Risk • Mortgage pricing

**JEL:** G21 • G28 • C19

## 1. Motivation

Systematic risk in bank lending is critical for mortgage portfolios as these dominate in volume and granularity. During the Global Financial Crisis (GFC), delinquency rates of prime mortgages nearly tripled, and the foreclosure rates doubled from 2007 to 2008 (Aubuchon et al., 2009). At the same time, the delinquency rate of subprime mortgages quadrupled (Mayer et al., 2009). These changes are systematic as most mortgages have been affected. Therefore, a thorough understanding of the sources of systematic risk is crucial for managing mortgage portfolios.

Systematic credit risk is commonly defined as the co-movement of observed default events and hence changes in default rates in granular loan portfolios. Standard industry practice assumes a single latent risk factor and does not allow us to disentangle the components comprising systematic risk. Due to this framework, the regulators set 15% as a systematic risk level for all residential mortgages. This hinders the recognition of the sources of systematic shocks. Our study unifies the two dominant systematic risk factors – observed and unobserved– to measure systematic risk components. We define failure beta (Beta) as the exposure level to the observed factor and asset correlation (AC) as the exposure to the unobserved (frailty) factor.

Current literature on systematic credit risk poses two drawbacks. First, previous papers focus on estimating the sensitivity to observed systematic risk factors (i.e., failure beta) but ignore the measurement of unobserved systematic risk levels. Second, unobserved variation is included at different interpretational levels, making benchmarking across industry models difficult. As a consequence, national regulators do not consider internal estimates for Beta and AC. Our study sets out to solve these problems.

We develop two-factor models to estimate Beta and AC to include common styles in the industry. The observed factor is measured by the mean probability of default (mean PD), and the unexplained variations of systematic risk are proxied by a set of time random effects. The observed factor is standardized to ensure the same interpretational level as the unobserved factor. We start the model aligning with the industry standard in which unobserved factor is the sole contributor to systematic risk and gradually incorporate observed factors.

In the first model (through-to-cycle model or TTC model), mean PD only reflects the impacts of loans and borrowers' characteristics at origination times, so the unobserved factors explain most of the systematic risk. In the second model (limited point-in-time model or lPIT model), we start introducing the time-varying variables into the estimation of mean PD, so the observed factor explains the observed component of systematic risk, and the unobserved factor explains the unobserved component. In the third model (comprehensive point-in-time model or cPIT model), we estimate the mean PD by incorporating macroeconomic effects resulting in a greater degree of observed systematic risk and a lower degree of unobserved systematic risk.

Using loan-level data on US securitized prime mortgages from 1999 to 2019 with approximately 20 million loans, we find that both observed and unobserved systematic risk factors drive mortgage defaults. When properly incorporating the observed systematic risk factors, the observed component outweighs the contribution from unobserved risk to the total systematic risk level. On average, the total systematic risk level is about 7% in relation to a theoretical value range between zero and one, of which the observed accounts for 75% and the unobserved accounts for 25%. Incorporating these two factors not only helps us to understand different sources of systematic risk thoroughly but also allows us to capture a higher level of systematic risk variations.

The levels of systematic risk components vary across different sub-samples of loans. Specifically, higher-risk mortgages have higher levels of systematic risk than lower-risk mortgages. We also find that mortgages in CA are more sensitive to systematic risk factors than in other states, which could be explained due to the stronger co-movements in California's real estate markets. Mortgages originated by non-bank lenders also carry a higher level of systematic risk. We hypothesize that these lenders have narrower lending policies and originate loan portfolios with greater homogeneity and hence greater exposure to systematic risk. This is empirically proved by higher concentration indexes (HHI) in the core loan characteristics such as FICO, LTV, and DTI of nonbank lenders compared to the traditional banks. The systematic risk levels of non-recourse mortgages are higher than those originating in recourse states. Non-recourse borrowers may be more likely to default strategically due to housing price shocks and hence be more exposed to systematic risk than recourse borrowers that are exposed to a combination of house price changes and idiosyncratic liquidity.

We further identify that lenders price systematic risk. The unexpected loss is computed based on the estimated Beta and AC and used as the proxy for the exposure to systematic risk. Through a horse-race regression, we find that a one-percent change in the Beta-related unexpected loss leads to approximately 4 four basis points (bps) of adjustment in the mortgage rate, which is double the change induced by the AC-related unexpected loss. We also compare the explanatory power using R-square between the exposure to our estimated systematic risk levels and the regulatory value of 15%. The finding indicates that the explanatory power is slightly higher when two systematic risk components are included than one regulatory component. This sensitivity analysis is made possible by the methodology developed in this paper.

Our paper makes several contributions to the literature. Firstly, our study develops a unifying framework for observed and unobserved systematic credit risk, allowing us to compare the influences of different systematic components empirically. Whilst we focus on mortgage loans, the framework may be generalized to other exposure classes. Secondly, our paper empirically estimates different systematic risk levels – Beta and AC – for different sub-samples of loans based on regions, lender types, and recourse types. Lastly, we directly test the role of systematic risk in mortgage pricing and provide evidence that lenders intuitively price systematic risk to some degree.

Our findings also carry practical implications for regulators and lenders. Regulators may revise regulations to incentivize systematic risk measurement, management, and optimization. Specifically, regulators do not distinguish between the level of systematic risk (a flat AC of 15% issued for mortgage loans) and whether risk measures such as default probabilities reflect Beta through so-called point-in-time ratings. With the evolution of fintech taking over the market share, regulation of non-bank lenders may be in reach.

For lenders, operating with a higher level of accuracy in risk measurement can open further opportunities for decision-makers to enhance their in-house models and competitiveness. Non-bank lenders have greater exposure to frailty risks and may be subjected to regulatory parameters as is currently in use for banks under Basel III regulations. Including lender-specific systematic risk may ultimately increase financial resilience.

This paper proceeds as follows. The following section reviews the relative empirical findings in the literature and develops the research hypotheses. Section 3 establishes a framework by constructing systematic risk measures and pricing systematic risk. Section 4 describes the data and constructions of variables. Section 5 presents and discusses the results of empirical tests, including payoff probability (PP) models, default probability (PD) models, measuring systematic risk levels, and the impact of systematic risk levels on mortgage rates. Finally, we deliberate the industry impacts in Section 6.

## 2. Literature review and research hypothesis

The literature has explored various sources of systematic risk for credit portfolio risk. The main feature of distinctions is observable and unobservable systematic risk. Most studies analyze the impacts/sensitivity of observed systematic risk factors on PD (stream 1), while fewer papers estimate the unobserved component of systematic risk levels (stream 2). In addition, most papers focus on corporate loans, and few analyze mortgage loans. Hilscher and Wilson (2017) have developed a framework to measure observed systematic risk for corporate loans. Lee et al. (2021) deconstruct and measure unobserved risk for mortgages. To date, no methodology exists that combines both measures and applies these to either corporate or mortgage loans. We summarize related papers in Table 1.

<Insert Table 1 here>

### 2.1. Observed systematic risk for mortgage loans

There is substantial literature on mortgage credit portfolio risk and the macroeconomy. Most research papers include macroeconomic variables as observed systematic factors in the PD models and predict mortgage defaults. For instance, Elul et al. (2010) examine the effects of unemployment on mortgage default probabilities; Amromin & Paulson (2009) and Crook and Banasik (2012) confirm the role of real estate prices as an essential risk driver; Goodstein et al. (2017), Gupta (2019), and Calabrese and Crook (2020) provide the empirical evidence on the positive effect of contagion factor amongst strategic defaulters.[1] The above studies highlight the impact of observed systematic factors on default probabilities but do not explicitly estimate the absolute exposure level of systematic risk.

Hilscher and Wilson (2017) measure the magnitude of observed systematic risk, albeit for different groups of corporate loans based on the rating. This is called failure beta, which is the

[1] There are many comparable papers for corporates. Pesaran et al. (2006) show that firms' default probabilities are determined by how strong the connection is between firms and business cycles and their interconnection in business cycles across the globe. Duffie et al. (2007) illustrate the prominent roles of S&P 500 returns and Treasury interest rates in predicting conditional future default probabilities.

sensitivity of firms' PDs to the median (or mean) PD. They find that the failure beta increases monotonically as the rating decreases. The median PD proxy is practical for lenders as they can easily estimate and capture the effect of observed systematic risk. We adopt this proxy in our paper and capture the fluctuations of observed factors through mean PDs. Instead of investigating the sensitivity to systematic risk factors, we further estimate the levels of systematic risks and examine their impacts on the pricing.

## 2.2. Unobserved systematic risk for mortgage loans

Systematic default risk may also be exposed to unobservable risk factors. The effects of these factors are often referred to as the frailty effects. Most of the research in this stream pays more attention to a corporate credit default.[2] The study of Jiménez & Mencía (2009) is among the first to develop a state space model to explain the default rates as the function of macroeconomic conditions and frailty risk factors in the Spanish banking system. They document the effects of macroeconomic factors on the expected exposures of default and identify the latent factors that drive the default density among different loan sectors. However, they do not estimate the systematic risk levels explicitly.

This stream of credit risk research on lending products estimates the unobserved systematic risk levels, usually defined as asset correlation. A high value of asset correlation indicates a strong interlink amongst borrowers, meaning that they are more dependent on the general state

[2] (Das et al., 2007) and (Duffie et al., 2009) analyze frailty effects for corporate default intensities and hence time clustering. They find that there is a significant gap between default prediction and the measured default intensities modelled by observable macroeconomic covariates such as Treasury bill rate or return of the S&P 500 stock index. Even after controlling for extra observable systematic factors, an excess degree of default correlation is still present. The other studies in this stream worth considering are (Dietsch & Petey, 2004), (Koopman et al., 2012), (Nickerson & Griffin, 2017). In a similar context, Azizpour et al. (2018) point out the role of the contagion effect on default clustering after controlling for macroeconomic and frailty factors and suggest that all three factors need to be included to achieve a better forecast of portfolio credit risk. However, they only provide the estimate of variance of default, and do not estimate the specific levels of exposure to different factors.

of the economy and more likely to default together in an adverse condition. The study of Calem & Follain (2003), managed by the Basel Committee, suggests the application of a 15% asset correlation assumption for mortgages on single-family residences. This rule was implicitly introduced in the Basel II rule in 2004 and has been widely applied in various banking systems, especially the G10 countries.[3] The recent study by Lee et al. (2021) specifies systematic risk as the unexplained variation of default rates and deconstructs it into general systematic risk and rating-class-specific systematic risk. Their findings show that the medium-risk classes are more exposed to the former component, while the lower and higher-risk classes are more sensitive to the latter. Further, the empirical values are lower than the Basel benchmark parameter of 15% for mortgage loans.

The literature has pointed out that default clustering exposes both observable and unobserved (frailty) systematic risk factors, which could vary across different sub-samples. Previous research illustrates the effects of systematic risk factors for mortgages, but no paper estimates the relative importance of both effects. By deriving a unifying framework, we are first to incorporate both observed and unobserved systematic risk factors on the same interpretational level. There is likely a disparity in systematic risk levels among different mortgage groups, hence we also measure the systematic risk levels for different samples based on lender types (banks vs. nonbank lenders), recourse types (recourse states vs. non-recourse states), and states (California vs. other states) in our study.

### 2.3. Pricing of mortgages

[3] Hashimoto (2009) estimates the asset correlation for corporate loans. They find out that asset correlation is higher for high- and low-risk companies, but lower for middle-risk ones.

Literature on pricing mortgage spreads is limited for fixed-rate mortgages as the interest rate is determined at the origination time and remains unchanged throughout loans' lifetimes. Lenders apply similar filtering standards to approve borrowers, which are likely risk-homogenous, and there is limited heterogeneity in mortgage interest rates. However, mortgage interest rates between lenders may differ due to different lending policies, risk appetites, and premiums for systematic risk levels due to concentrations. As systematic risk is strongly linked to the capital cost of lenders, it should be reflected in the mortgage spread.

Rajan et al. (2015) conduct a year-by-year regression and find that the mortgage interest rate strongly relates to FICO and LTV over time. Antinolfi et al. (2016) describe the mortgage rates as a function of loan and borrower characteristics such as LTV, FICO, and loan amount. Levitin et al. (2020) find that mortgage rates are less likely to be influenced by loan and borrower characteristics during the housing bubble. The literature has shown that loan prices and borrower characteristics are related. Benetton et al. (2021) find a positive relationship between mortgage rate and capital requirements. Justiniano et al. (2022) discover a disconnect between mortgage interest rates and Treasury yields, which makes mortgages more affordable. The recent study by Nguyen et al. (2022) documents the positive relation between mortgage spreads and exposure to sea-level rise risk even after controlling for flood insurance. We argue that this climate exposure may manifest a form of systematic risk, so we expect a similar connection between mortgage spreads and our measures of systematic risk.

The positive relationship between systematic risk levels and risk premium are well-documented in the literature for tradeable securities such as stocks (Fama & French, 2015), corporate bonds (Bai et al., 2019), options (Duan & Wei, 2009), futures contracts (Bessembinder, 1992), CDS (Wang et al., 2013), etc.

However, the pricing of systematic risk for mortgages has received much less attention. Therefore, we seek to answer how much systematic risk levels can explain the mortgage rate variations in our study. To the best of our knowledge, our study is the first to price the mortgage spreads against the systematic risk levels. We believe our results will have important implications for the pricing of mortgage loans in financial institutions going forward.

## 3. Framework

We proceed in four stages. Stage 1 models probabilities of prepayment/payoff (PPs). Stage 2 models the probabilities of default (PDs) whilst controlling for PPs. In Stage 3, we estimate observed systematic risk using Beta and unobserved systematic risk using AC based on PDs from Stage 2. In Stage 4, we develop a regression model to test the price impact of the exposure to systematic risk.

### 3.1. Probabilities of payoff (Stage 1)

We estimate a probability of payoff (PP) model to explain the payoff outcomes, which in turn impact probabilities of default based on the creditworthiness[4] $V_{it}$ of borrower *i* in time *t*. Payoff occurs if a random trigger variable $V_{it}^P$ falls below a deterministic threshold $\lambda_{it-1}^P$. The subscript -1 expresses that information is observed prior to this process:

$$P_{it} = \begin{cases} 1, V_{it}^P < \lambda_{it-1}^P \\ 0, V_{it}^P \geq \lambda_{it-1}^P \end{cases} \tag{1}$$

We model PP as a probit model for a respective threshold:

$$PP_{it} = P(P_{it} = 1) = \Phi(\lambda_{it-1}^P) \tag{2}$$

[4] Credit worthiness is sometimes called the asset return following the early days terminology of the FOM and related to Merton model.

where $\Phi(\lambda^{P}_{it-1})$ is the standard normal cumulative density function. The default threshold expressed as $\lambda^{P}_{it-1}$ is a function of $X_{it-1}$ which are the set of information on loan and borrower characteristics.

We use annual observations for our regressions since default events are usually recorded at the yearly interval as industry practice. The estimated PPs enter our Stage 2 regressions for PD to control selection bias induced by the payoff decision of borrowers. The distribution of observations over categories of the independent variables may be driven by a selective process in which payoff loans have distinctive features compared to default loans.

PPs and PDs can be estimated by different factor models that may be stylized in through-to-cycle (TTC) models and point-in-time (PIT) models. According to the Basel Accord, banks can build internal PD models based on a TTC concept to limit procyclical effects on capital requirements. PIT models are generally timelier and hence accurate than TTC models as they include time-invariant idiosyncratic information, time-varying idiosyncratic and macroeconomic factors.

We estimate three models. First, a TTC model includes information at the origination time only. Second, a limited PIT model adds time-varying variables related to loans and borrowers, including change in LTV, loan age, and square of loan age next to the information at the origination time from the TTC model. Third, a comprehensive PIT model adds the macroeconomic factors – change in HPI and change in the unemployment rate.[5] Including these two variables enables the comprehensive PIT model to capture the exposure to observed systematic risk thoroughly.

[5] We do not incorporate the contagion effect in the comprehensive PIT model because this factor tends to have impact on strategic defaulters only (Borrowers tend to go default if being adversely impacted by house price fluctuations). In other words, the contagion effects may align with the housing risk. The measurement of this factor in the literature is localized at zip code level which could be overlapped with the measure of LTV change in our model.

We include state dummies in all models to control for the state fixed effects. In the PIT models, we include vintage dummies to control the overall economy at origination time. We use the subscript $\tau$ for all variables collected at the origination period and subscript $t$ for variables collected at the current time. The subscript -1 expresses that information is observed prior to the process.

The three PP model specifications are:

$$PP_{TTC}(P_{it} = 1) = \Phi(\alpha_P + \beta_P OrigX_{i\tau}) \tag{3}$$

$$PP_{lPIT}(P_{it} = 1) = \Phi(\alpha_P + \beta_P OrigX_{i\tau} + \theta_P CurrX_{it-1}) \tag{4}$$

$$PP_{cPIT}(P_{it} = 1) = \Phi(\alpha_P + \beta_P OrigX_{i\tau} + \theta_P CurrX_{it-1} + \delta_P Macro_{t-1}) \tag{5}$$

where $P_{it}$ is the payoff indicator; OrigX are variables at the origination time including FICO score, orig LTV, orig DTI, and dummy variables indicating loan purpose, number of borrowers, property types, origination channel and mortgage insurance requirement; CurrX represents time-varying characteristics such as change in LTV, loan age and square of loan age; Macro consists of change in HPI and change in unemployment rate.

### 3.2. Probabilities of default (Stage 2)

The set-up of PD model explains the creditworthiness[6] $V_{it}$ of borrower *i* in time *t*. Default occurs if $V_{it}$ falls below a default threshold $\lambda_{it-1}$. The subscript -1 expresses that information is observed prior to the process.

$$D_{it} = \begin{cases} 1, V_{it} < \lambda_{it-1} \\ 0, V_{it} \geq \lambda_{it-1} \end{cases} \tag{6}$$

We derive the unconditional PD model given a standard normal distribution for $V_{it}$ as:

[6] Credit worthiness is sometimes called the asset return following the early days terminology of the FOM and related to Merton model.

$$PD_{it} = P(D_{it} = 1) = P(V_{it} < \lambda_{it-1}) = \Phi(\lambda_{it-1}) \tag{7}$$

where $\Phi(\lambda_{it-1})$ is the standard normal cumulative density function. The default threshold expressed as $\lambda_{it-1}$ is a function of $X_{it-1}$ which are the set of information on loan and borrower characteristics including the proxies for negative equity and illiquidity as indicated in the DTM theory, the macroeconomic conditions, and payoff probability (PP).

The three PD specifications are:

$$PD_{TTC}(D_{it} = 1) = \Phi(\alpha_D + \beta_D OrigX_{i\tau} + \gamma_D PP_{it}) \tag{8}$$

$$PD_{lPIT}(D_{it} = 1) = \Phi(\alpha_D + \beta_D OrigX_{i\tau} + \theta_D CurrX_{it-1} + \gamma_D PP_{it}) \tag{9}$$

$$PD_{cPIT}(D_{it} = 1) = \Phi(\alpha_D + \beta_D OrigX_{i\tau} + \theta_D CurrX_{it-1} + \delta_D Macro_{t-1} + \gamma_D PP_{it}) \tag{10}$$

where $D_{it}$ is the default indicator and $PP_{it}$ are the estimated PPs from the Stage 1 regressions

The list of variable descriptions is as follows:

<Insert Table 2 here>

### 3.3. Measures of systematic risk (Stage 3)

The dominant model for systematic risk in credit risk is the asymptotic single risk factor (ASRF) model or Vasicek model, where the default trigger variable $V_{it}$ is driven by a standard normal systematic factor $F_t$ and a standard normal idiosyncratic factor $U_{it}$:

$$V_{it} = \sqrt{\omega} F_t + \sqrt{1-\omega} U_{it} \tag{11}$$

The loading $\omega$ is known as the asset correlation, and the parameterization is chosen so that $V_{it}$ is also standard normal. It can be shown that different parameterizations result in identical empirical estimates.

We extend the ASRF model by decomposing the systematic risk into a two-factor model, which explains the creditworthiness as a linear function of observed systematic risk ($S_t$), unobserved systematic risk ($F_t$), and idiosyncratic risk ($U_{it}$).

$$V_{it} = \sqrt{\beta}S_t + \sqrt{\omega}F_t + \sqrt{1-\beta-\omega}U_{it} \tag{12}$$

Following the ASRF, we assume that $S_t$, $F_t$ and $U_{it}$ are independent and identically standard normally distributed. This assumption implies that the variance of asset value which is also the measure of total risk is equal to one.

$$\sigma = var(V_{it}) = \beta + \omega + \gamma = 1 \tag{13}$$

Where $\beta$ and $\omega$ measure systematic risk levels, and $\gamma$ represents for idiosyncratic risk.

The total systematic risk level will be the sum of $\beta$ and $\omega$. To align with the literature, we name these two sources of systematic risk as *Beta* and *asset correlatio*n (AC), respectively. We can estimate Beta and AC through a conditional PD (CPD) model. We derive the CPD model as follows:

$$\begin{aligned} CPD_{it} = P(D_{it} = 1|S = s, F = f) &= P(V_{it} < \lambda_{it-1}|s_t,\ f_t) \\ &= \Phi\left(\frac{\lambda_{it-1} - \sqrt{\beta}s_t - \sqrt{\omega}f_t}{\sqrt{1-\beta-\omega}}\right) \\ &= \Phi\left(\frac{\lambda_{it-1}}{\sqrt{1-\beta-\omega}} - \frac{\sqrt{\beta}}{\sqrt{1-\beta-\omega}}s_t - \frac{\sqrt{\omega}}{\sqrt{1-\beta-\omega}}f_t\right) \\ &= \Phi(a * \lambda_{it-1} + b * s_t + c * f_t) \qquad (14) \end{aligned}$$

Where $\lambda_{it-1}$ is the idiosyncratic risk factor, $s_t$ is the observed systematic risk factor and $f_t$ is the unobserved systematic risk factor. The two systematic factors are standardized to be able to compare their magnitudes. The coefficients of the CPD model are reparametrized to match the regression parameters:

$$a = \frac{1}{\sqrt{1-\beta-\omega}};\ b = -\frac{\sqrt{\beta}}{\sqrt{1-\beta-\omega}};\ and\ c = -\frac{\sqrt{\omega}}{\sqrt{1-\beta-\omega}} \tag{15}$$

Beta ($\beta$) and AC ($\omega$) are estimated as follows:

$$\hat{\beta} = \frac{\hat{b}^2}{1+\hat{b}^2+\hat{c}^2};\ \hat{\omega} = \frac{\hat{c}^2}{1+\hat{b}^2+\hat{c}^2} \tag{16}$$

Following Hilscher & Wilson (2017), we employ mean PDs by time as the proxy for the observed systematic component. Systematic risk is defined as the variation in the average default rate. We control the influences of idiosyncratic risk factors related to loans and characteristics on default clusters consistent with Das et al. (2007) and Lando & Nielsen (2010). Moving from the TTC model to PIT models, more time-varying covariate and macroeconomic factors are added to explain PDs with the consequence that PDs will reflect more volatilities in the average default rate. We expect the observed systematic variation to be the smallest for the TTC model and the largest for the comprehensive PIT model.

We employ the set of time (year) dummy variables to represent changes in business cycles through time and impose the normal distribution to estimate the exposure to unobserved systematic risk. The unobserved component measures the business cycle condition which is left unexplained by observed risk factors (residual systematic variation) and is also known as frailty. We expect the unobserved systematic risk level to be the largest for the TTC model and the smallest for comprehensive PIT models. We estimate the CPD model specified in Eq. (14) through a nonlinear mixed model with a quasi-Newton algorithm. The dependent variable (i.e., default rate) is transformed to the probability using the probnorm function. Mortgage lenders can replicate this approach.

We also estimate the CPD models for subsamples that are based on several criteria, such as lender types (bank vs. nonbank), recourse types (recourse vs. non-recourse states), and states (California vs. nine others). To ensure that the impacts of observed and unobserved systematic risk factors on loans from different groups are comparable, we adjust Eq. (14) by including the dummy variables for group classification and their interactions with the systematic components in the models. This method allows us to concurrently estimate the exposures to observed and unobserved systematic factors of two or more groups. The CPD model is now designed as follows:

$$CPD_{it} = P(D_{it} = 1 | S_t = s_t,\, F_t = f_t)$$
$$= \Phi\big(a_0 * \lambda_{it-1} + \textstyle\sum_{k=1}^{k}(a_k * \Delta_{it}) + b * s_t + \sum_{k=1}^{k}(c_k * s_t * \Delta_{it}) + d * f_t + \sum_{k=1}^{k}(e_k * f_t * \Delta_{it})\big) \quad (17)$$

where $\Delta_{it}$ represents the dummy variables, $k$ is the number of dummy/interaction variables less one (for the reference category).

For region, lender, and recourse types, there are two groups of loans in the sample (CA vs. other states, banks vs. nonbank lenders, and recourse vs. non-recourse states), so one dummy and one interaction term are added to the model.[7] Class-specific Beta ($\beta$) and AC ($\omega$) will be computed from the estimated parameters as follows:

$$\hat{\beta}_0 = \frac{\hat{b}^2}{1+\hat{b}^2+\hat{d}^2};\ \hat{\omega}_0 = \frac{\hat{d}^2}{1+\hat{b}^2+\hat{d}^2} \quad (18)$$

$$\hat{\beta}_k = \frac{(\hat{b}+\hat{c}_k)^2}{1+(\hat{b}+\hat{c}_k)^2+(\hat{d}+\hat{e}_k)^2};\ \hat{\omega}_k = \frac{(\hat{d}+e_k)^2}{1+(\hat{b}+\hat{c}_k)^2+(\hat{d}+\hat{e}_k)^2} \quad (19)$$

where reference groups are California, nonbank lenders, and non-recourse states.

Instead of estimating the CPD model with a default indicator, we obtain the default rates for each subsample and time and run Eq. (17) to reduce the computational burden.

### 3.4. Pricing tests (Stage 4)

Liu et al. (2012) use data at issuance and find the relationship between the spread of debt contracts and recovery rates. In this sense, we analyze whether the mortgage interest rates reflect the impact of systematic risk at origination. We measure the exposure to systematic risk level as the unexpected loss, which is the basis for lender capital and funding costs. The

[7] We also estimate the systematic risk levels for risk classes in the robustness test. Ten risk classes are formed, hence nine dummies and nine interaction terms will be added to the model. The reference group is the lowest-risk class.

unexpected loss is calculated as the difference between the 99th percentile of the CPD (i.e., VaR) and the expected loss. This is also considered the capital requirement for lenders to remain solvent over a one-year horizon.

$$UL_{srisk} = \Phi\left(\frac{\Phi^{-1}(PD)+\sqrt{srisk}\Phi^{-1}(0.999)}{\sqrt{1-srisk}}\right) - PD \tag{20}$$

Where $\Phi^{-1}(PD)$ is the inversed function of unconditional PD returning the linear combination of logistic regression estimated in either Eq. (5), (7) or (9); *srisk* is the exposure to systematic risk factors, which could be Beta, AC or total risk; *99.9%* is the conservative value of single systematic risk factor according to Basel III to represent the state of the global economy.

To create more heterogeneity in systematic risk levels, we randomly split mortgages into sub-samples with approximately 10,000 loans each and estimate systematic risk levels for each sub-sample. As a result, we obtain around 2,000 sub-samples and have 2000 variations of unexpected loss for the pricing regression.

Loan-level prices may be based on loans and borrowers' characteristics according to underwiring criteria. Therefore, we add FICO, DTI, LTV, loan size, dummy variables for property type (single-family house or others), loan purpose (purchased or refinancing), number of borrowers (one or more), origination channel (retail or third-party originator), occupation status (investment or residency), and mortgage insurance. We include the national average rate on a 30-year mortgage[8] in the pricing equation. This allows us to capture the variations in mortgage rates compared to the national rate as well as vintage effects. We also include state dummy variables to control state regulation and lending competition. Standard errors are clustered by lender to control for the lending standard[9]. We define the pricing regression as follows:

[8] We collect the data on national average rate on 30-year mortgages from FRED St. Louis FED database https://fred.stlouisfed.org/series/MORTGAGE30US

[9] We remove observations with missing observations in lender name which is approximately 1.8 million loans. This leaves us more than 18 million loans in the sample for the pricing tests.

$$Int\_rt_{i,\tau} = \alpha + \beta UL_{srisk,i} + \gamma Rate_\tau + \delta X_{i,\tau} + \eta_s \quad (21)$$

where UL is unexpected loss reflecting the borrower's exposure to the systematic risk factor, Rate is the national average of a 30-year mortgage; X represents the loan and borrower characteristics, $\eta_s$ represents the state dummies.[10] All observations are recorded at the origination time.

## 4. Data description

We obtain data on mortgage loans from the Federal Housing Finance Agency (FHFA), which includes information on mortgage contract characteristics at the origination period and monthly loan performance. The mortgages are originated by banks and non-banks and securitized by the US Federal Home Loan Mortgage Corporation.[11]

The original data set consists of more than 1.4 billion observations at monthly intervals from February 1999 to December 2019. Since mortgages with different maturities may have different term premiums, we restrict our analysis to only 30-year fixed-rate mortgages. We also dropped observations where the information on borrowers and loan characteristics such as FICO, DTI, LTV, occupancy status, number of borrowers, property type, loan purpose, and origination channel is unavailable. Furthermore, we exclude mortgages that were financed for investment purposes, second homes, and those with a prepayment penalty.[12] Loans ceasing their existence in the sample due to third-party or reperforming sales are excluded. After recording the default events of loans that were delinquent for 90 days or more or involved in foreclosure events, we

[10] We also run the piecewise Linear Regression which the spline expansions of continuous variables. The results remain robust.

[11] FDIC (2019)states that banks sold nearly half of their 1–4 family originations, while nonbanks sold more than 97 percent.

[12] Loans supporting for investment account for 6.13% and loans with prepayment penalty only account for 0.11% in the full sample.

immediately removed the loans from the data set. After all filter rules, the final sample is reduced to around one billion observations.

We aggregated the monthly data into an annual sample as many industry metrics are based on a one-year reporting period. We take the average values for metric variables such as FICO score, DTI, LTV, loan balance, loan age, and interest rate. The HPI data at the zip code level is merged into the annual sample, and current house values are imputed as the product of the original house value and the ratio of current HPI and original HPI. We exclude observations with missing current house values. Finally, the national HPI and UER at annual intervals collected from the Federal Reserve Bank of St. Louis database are merged, and their percentage changes are computed. Our annual sample from 1999 to 2019 consists of 99,151,998 observations, covering approximately 20 million loans.

In total, we observed 1,075,584 default events representing an average default rate of roughly 1.07%, and 14,534,452 payoff events, equivalents to a payoff rate of 14.44%. Table 3 shows the default rate and payoff rate for categorical variables.

<Insert Table 3 here>

Refinance mortgages and the ones with a single borrower, non-single-family homes and loans originated through third-party (TPO) channels have a greater default rate. Mortgage-insured loans also have a greater default rate as these borrowers are required to obtain a costly mortgage insurance. This helps mitigate loss given default but increases the risk for the additional expense.

In short, we detect that loans that are refinanced, have one borrower, support for single-family homes, involve in third-party origination, and require mortgage insurance have a higher default rate than their counterparts. We expect that these attributes will have a positive effect on the probability of default. In contrast, there is only a minor difference in payoff rates across various groups of loans. Most groups have an average payoff rate of 14% per annum.

Considering the changes in default rate and payoff rate over the sample period, most of the default events occurred during the crisis period between 2008 and 2010. The peak is reached with 438,903 events, equivalent to a default rate of 2.317%. This affirms the existence of default clustering and mortgage exposures to systematic risk factors. Furthermore, loans originated just before the GFC (from 2005 to 2007) have the highest default rate of 2.4%. This reveals the relaxed lending standards during the pre-crisis (Dell'Ariccia et al., 2012).

Table 4 provides the descriptive statistics for metric variables FICO, original DTI, original LTV, LTV_change, loan age, and macroeconomic variables. The average FICO score is 731, which is considered to be a good credit rating. The average original DTI is 34.1%, which means that 34.1% of borrowers' income is spent on paying mortgage debt, making it one of the biggest spending categories for households. The original LTV is 74% (the median is roughly 80%), reflecting a standard requirement from banks that borrowers are usually required to have at least 20% of the house value as a deposit. Meanwhile, the change in LTV is around -10% due to amortization and house price gains. Current LTVs may have increased due to house price losses during the GFC. The average loan age in our sample is 3.2 years, and the maximum loan age is slightly more than 20 years. Although our sample consists of 30-year fixed-rate mortgages, most of them are paid off before maturity. Regarding macroeconomic variables, HPI has increased on average by 2.4%, and the unemployment rate also increases by around 1.4% per year.

<Insert Table 4 here>

We also observe the average values of metric variables for default and payoff sub-samples. Payoff loans have higher FICO, lower LTV, and lower DTI than default loans. These findings support the DTM, where loans with higher liquidity (DTI) and leverage (LTV) are more likely to default and less likely to refinance or payoff loans.

## 5. Empirical results

### 5.1. Probabilities of payoff

In this section, we present the estimation results of the PP models in Table 5 based on probit regressions.[13]

A higher default risk corresponds to a lower payoff risk. We find that the coefficients on original LTV and LTV_change are both negative. This suggests that a higher LTV, possibly driven by a drop in house price, reduces the refinance and hence payoff likelihood. Original DTI has a positive sign which suggests that borrowers with a higher DTI may be more motivated to pay off or refinance their loans to reduce their interest payments. The unemployment rate – a proxy associated with illiquidity – has a negative effect on PP, meaning that job losses may restrict borrowers from paying off. The coefficients on other loan and borrower characteristics are consistent with the literature. Regarding model fit, the AUROC and R-square values constantly increase from the first to the last models, meaning that a more complex model doubtlessly explains more variations in payoff rate.

<Insert Table 5 here>

### 5.2. Probabilities of default

We display the estimation results for PD models in Table 6. All estimates are highly consistent across the three models and follow the directions suggested by the descriptive analysis. Lower FICO scores, higher LTV, and higher DTI ratios have lower PDs. These results are consistent

[13] We obtain the consistent results when employing multinomial logit regression.

with numerous studies in the literature (Mayer et al., 2009; Elul et al., 2010; Chan et al., 2016). In addition, we certify that refinanced loans, loans with single borrowers, loans supporting non-single-family houses, loans originating through a third party, or those whose borrowers are required to obtain mortgage insurance are riskier and have a greater PD.

<Insert Table 6 here>

The results are as expected regarding the impact of time-varying factors. The coefficients on change in LTV are positive in all models. This indicates that an increase in LTV likely induced by a drop in house value raises the PD. In other words, an increase in the house price index leads to a rise in home equities, supporting borrowers to make loan payments. This explains the negative coefficient on change in HPI. In contrast, borrowers may not continue serving the loans if the unemployment rate surges. These empirical results support the DTM theory.

The model fit measured by the AUROC ratio increases from 77.8% in the TTC model to 84.5% in the most comprehensive PIT model. The Pseudo R-square improves from 9.7% to 16.9% across three models. The more complex model again proves to be a better candidate to explain the variations in default rates. Since we proxy the systematic risk by the variations of the average PD and hence default rate, we argue that a more complex PD model is also superior to the TTC model in capturing observed systematic risk factors. We demonstrate this by showing movements of default rate and mean PD over time across three models.

<Insert Figure 1 here>

The TTC model's average PD is relatively flat and slightly decreases after 2008 due to the tightened lending standards on mortgages after the housing bubble burst in 2007. Obviously, the estimates from the TTC model do not align with the default rate. Rajan et al., (2015) acknowledge a poor model performance in predicting loan creditworthiness. Mean PD of the limited PIT model is more aligned with the default rate as being adjusted by the macroeconomic state at the origination time and change in local HPI. However, this model could not properly capture the fluctuations in the default rate. With the inclusion of macroeconomic factors such as a change in national HPI and unemployment rate, the comprehensive PIT model is best suited for predicting default as the dashed lines showing the average of PD follow the solid line of default rate closely.

## 5.3. Measures of systematic risk

### 5.3.1. Full sample

Our main analysis aims to measure the levels of systematic risk in residential mortgages. Through the CPD model, we estimate *Beta* as the observed systematic level and *AC* as the unobserved (latent) systematic level. Table 7 presents the regression of the CPD model in Panel A and the additional estimates for systematic risk levels in Panel B. We have three CPD models, which differ from the observed systematic risk factor proxy - the mean PDs obtained from the corresponding unconditional PD models.

<Insert Table 7 here>

In the TTC model, where the observed systematic risk factor does not capture the macroeconomic condition, we find that the unobserved factor is the principal contributor to the systematic risk level. The coefficient on this factor is estimated at 0.261, indicating that an increase of one standard deviation unit leads to an increase of 26.1% in default rate. Meanwhile, the coefficient on the observed counterpart is not statistically significant. As we control for more macroeconomic factors in the following models, the observed effect becomes more prominent in explaining the variation of default rates. The frailty effect reduces in magnitude but remains meaningful. We find in the comprehensive PIT model that the coefficient on the observed factor is 0.246 while that on the frailty factor is 0.138.

We reparametrize systematic risk levels based on the sensitivity to systematic risk factors Beta and AC. As we move from the TTC model to the PIT models, we find that Beta significantly increases from 0 to 5.6%, and AC decreases from 6.4% to 1.8%. In the comprehensive PIT model, we indicate that Beta contributes explicitly 76% and AC contributes 24% to the total systematic risk levels. The total systematic risk has increased from 6.4% in the TTC model to 7.4% in the comprehensive PIT model. As the variance of the default rate is estimated at 10.28%, the sum of Beta and AC can explain roughly 70% of the default clustering. Even though the total systematic risk is always a combination of two components, incorporating the observed factor into the CPD model instead of relying on a single unobserved factor improves the predictive accuracy of PDs. We visualize the changes in Beta and AC across three models in Figure 2.

<Insert Figure 2 here>

We demonstrate the changes in observed and unobserved factors over the sample period across three models in Figure 3. The frailty factor acquires the remaining fluctuations in the business cycle left by the observed factor. The observed systematic risk factors do not fully reflect the macroeconomic conditions in the TTC and limited PIT models; hence the frailty factor plays an important role in capturing the default clustering and aligns with NBER recession periods.

<Insert Figure 3 here>

In the comprehensive PIT model, the observed factor reflects the impacts of housing market volatility and the unemployment rate. The residual frailty factor shows more noise. We notice minor spikes in frailty factors in 2005 and 2017, which the observed factor could not explain. These demonstrate a rise in default variations due to a lowering of lending standards in 2005 (Koopman et al., 2012).

#### 5.3.2. Sub-sample analysis

We now implement the estimation for multiple sub-samples to examine whether different groups of loans have different exposures to systematic risk factors. We present the estimations for in Table 8. Three panels in Table 8 show the following results: Panel A is for banks and nonbank sub-samples, Panel B is for recourse and non-recourse sub-samples, and Panel C is for California and other states. Consistent with the main results, the unobserved factor is the dominant factor in explaining default clustering in the TTC model but becomes less important after controlling for the observed systematic risk factor.

<Insert Table 8 here>

*Lender types*

We analyze the systematic risk levels in mortgages originated by banks and nonbank lenders.[14] The exposure to the observed factor is more potent for banks, while the exposure to the unobserved factor is more substantial for nonbank lenders. The total systematic risk levels are comparable between banks and nonbank lenders in the partial models. However, we notice a higher total systematic risk level in nonbank mortgages than bank mortgages in the comprehensive PIT model, where both systematic risk factors are properly incorporated.

The study by Demyanyk & Loutskina (2016) shows that nonbank lenders are more likely to relax their lending standards and originate mortgages to riskier borrowers. They are also not under strict regulatory oversight as compared to banks Irani et al. (2021). Their funding sources rely on the short-term line of credit provided by banks, so the variations in funding costs may harm borrowers, leading to a higher delinquent rate (Kim et al. (2018). As a result, nonbank mortgages may be more sensitive to systematic risk. Furthermore, the HHI indexes based on

[14] Banks are defined as depository institutions including credit unions and savings associations. Nonbanks are mainly mortgage companies. Other nonbank lenders can be subsidiaries of bank holding companies, finance companies or real estate investment trusts. We check the description of their business lines on Bloomberg/their website/SEC to decide whether the lenders are bank or nonbank. In sum, we have 68 nonbank lenders and 38 traditional banks in our sample.

the core loan characteristics such as FICO, LTV, and DTI are higher for nonbank lenders than traditional banks.[15] This reveals that nonbank loan portfolios are narrower and more concentrated than banks, resulting in originations of more homogeneous diversifying idiosyncratic risk.

R*ecourse types*

Next, we investigate the systematic risk levels of mortgages between recourse and non-recourse states. Recourse lenders have access to the collateralizing house and the general borrower assets. Hence, borrowers default if they encounter negative equity and liquidity constraints. Non-recourse lenders have only access to the collateralizing house and borrowers default if they experience negative equity. Non-recourse mortgages potentially have higher systematic risk levels than recourse mortgages as the defaults are more driven by systematic risk housing markets (see Cotter et al. (2015)).

Our results show that in all three models, Beta and AC of mortgages in non-recourse states are consistently higher than those in recourse states. As a result, the total systematic risk levels of non-recourse mortgages are greater than those of recourse mortgages. This finding is aligned with Ghent & Kudlyak (2011) and Elul & Tilson (2016).

*States*

We continue estimating the exposure to systematic risk at the state level as the various state-related macroeconomics may exert different impacts on systematic default risk. Cotter et al. (2015) find that California's housing market is exposed to the greatest risk compared to the

[15] FICO-related HHI is 10.4 for nonbank lenders and 10.1 for banks. LTV-related HHI is 14 for nonbank lenders and 13.5 for banks. DTI-related HHI is 10.2 for nonbank lenders and 10.1 for banks.

other regions. Since mortgage default is closely linked to housing market volatility, we estimate the systematic risk levels between California and other states.[16]

We find that the estimations of Beta and AC are much higher for California than in other states, which is strongly consistent with Cotter et al. (2015). Our finding can be explained by the higher housing market risk in California and the nature of a non-recourse state which is more sensitive to systematic risk factors.

## 5.4. Pricing impact of systematic risk level

### 5.4.1. Full sample

Table 9 reports the regression results examining the impacts of the exposures to systematic risk components on the mortgage rate. We compare our estimation results with the regulatory framework, where a benchmark of 15% is widely applied to calculate the unexpected loss. We find that the variations in mortgage rates are positively related to the exposure to systematic risk levels. The exposure levels to two systematic components differ according to the degree of observed factors included in the model.

<Insert Table 9 here>

In the TTC model in Column 1, most systematic risk exposure is explained by the AC, and hence unobserved factors solely explain the systematic risk. The coefficient on the UL generated from Beta is not statistically significant, while that on the AC-induced UL is significant at 0.0196. The regulatory model could be comparable to the TTC model due to the similar assumption that the latent factor dominates the systematic risk exposure. Although the explanatory powers between the two models are indifferent with similar R-square values, we

[16] We also adopt Cotter et al. (2015)'s regional category and estimate the systematic risk levels at regional level. The results consistently show that mortgages in California are more exposed to systematic risk and have a higher systematic risk level for both Beta and AC. We present the results in the Appendix A.

notice a stronger sensitivity of mortgage rate to the exposure based on the estimated AC than the regulatory value. In particular, a one-percent increase in the UL induced by AC leads to an increase of roughly two bps in the mortgage rate, while a similar increase in the UL caused by the regulatory value leads to a rise of 1.5 bps in the mortgage rate. This finding could suggest the use of the in-house estimations from the lenders for a better pricing model.

For the limited PIT model in Column 2, both coefficients on systematic risk components are positive (0.0318 for Beta-related UL and 0.0162 for AC-induced UL) and statistically significant. The mortgage rate is more exposed to the observed component than the unobserved one. In particular, a one-percent increase in the unexpected loss (i.e., $UL_{Beta}$) leads to a rise of 3.2 basis points (bps) in the mortgage rate, but a similar increase in the $UL_{AC}$ only results in half of the magnitude (1.6 bps).

When moving to the comprehensive PIT model in Column 3, the mortgage rate is only related to the observed component only (the coefficient on $UL_{Beta}$ of 0.045 at the 1% level). A one-percent increase in the UL based on Beta results in a jump of 5 bps in the mortgage rate. The coefficient on the unobserved component is not statistically significant. We also look at R-square to examine the explanatory power across three models (i.ed. higher R-square, better model). Moving from the TTC model to the cPIT model, the R-square increases from 88.09% to 88.19%, which indicate that the comprehensive PIT model is the best for explaining the variations in mortgage rates. This finding signifies the crucial role of observed risk in determining the mortgage rate.

In summary, systematic risk is priced in the mortgage rate. The observed risk factor plays a more critical role than the unobserved risk factor in explaining the variations in mortgage rates. In addition, incorporating both risk factors helps boost pricing accuracy compared to a single-factor regulatory framework. Our findings pave the way for mortgage lenders to achieve a better pricing scheme.

### 5.4.2. Sub-sample

Table 10 presents the pricing results for different sub-samples, including banks vs. nonbank lenders (Panel A), non-recourse states vs. recourse states (Panel B), and CA vs. other states (Panel C). At first glance, all coefficients on systematic risk components are positive, indicating the relevance of including systematic risk in mortgage pricing. The exposures of mortgage rates to systematic risk components vary across different sub-samples.

<Insert Table 10 here>

The results for different lenders presented in Panel A show that mortgages issued by banks are more sensitive to the observed systematic risk, but those originated by nonbank lenders show a stronger sensitivity to the unobserved systematic risk. In the TTC model where the unobserved factor takes the dominant role, a one-percent increase in the unexpected loss induced by AC causes a rise of 1.6 bps for nonbank mortgages and less than one bp for bank mortgages. A similar increase in the comprehensive PIT model where the observed factor takes the leading role generates a 3.8 bps for nonbank mortgages and 4.2 bps for bank mortgages. With the current industry practice assuming an unobserved factor as the single shock to the systematic risk, nonbank lenders may charge higher interest rates for mortgages to compensate for the higher level of systematic risk. If properly incorporating both systematic factors in the model, bank mortgages tend to be higher than nonbank mortgages. This is because banks are subjected to heavy regulation and need to charge a higher interest rate to cover the capital requirement.

The results for different types of recourse law in Panel B are consistent with the main analysis. The exposure to the unobserved factor takes the dominant role in explaining the variations of mortgage rates in the TTC model but becomes less important when more observed factors are incorporated in the PIT models. As we move from the TTC model to the cPIT model, the magnitudes of coefficients on $UL_{Beta}$ increase and those on $UL_{AC}$ decrease for both recourse and nonrecourse subsamples. However, we notice that the unobserved factor remains effective on the non-recourse mortgage rates even after the observed factor is fully incorporated. This finding signifies the importance of including two pricing factors for nonbank lenders.

Regarding the pricing impact on mortgages across states (Panel C), our empirical evidence suggests positive relationships between mortgage rates and exposures to systematic risk factors. However, there is a slight divergence in the state-level results compared to the main analysis. The regressions for other states depict a common finding in which the pricing impact of Beta-related exposure increases and that of AC-related exposure decreases from the TTC model to the PIT models. For CA mortgages, both systematic factors' contributions in explaining the variations of mortgage rates increase as we move from the simple model to more comprehensive ones. The possible explanation for the CA result applies to the nature of being a non-recourse state. We believe the unobserved factor remains effective even after fully incorporating the observed factor. Despite that, the observed effect outweighs the unobserved counterpart.

## 5.5. Robustness tests

### 5.5.1. Using different default indicator

We now change the default definition to delinquencies over 60 days in addition to foreclosure. This definition increases the number of default events as well as default rates. We replicate the estimation for the full sample and summarize the result in Panel A of Table 11. The results are consistent with the main finding where the influence of Beta (AC) in driving systematic risk levels gets stronger (weaker) as we move from the TTC model to the PIT models. However, the total systematic risk level is smaller than for delinquencies over 60 days as these delinquencies include idiosyncratic factors (e.g., forgetfulness) to a greater extent than systematic factors. This could be because the early-delinquent borrowers have a level of resilience to the point that they can recover and solve the initial problem. However, the contributions of Beta and AC remain consistent, where Beta is still the dominant component when properly controlling both factors.

<Insert Table 11 here>

### 5.5.2. Using the first principal component as the proxy for observed systematic risk factor

We replace the proxy of the observed systematic risk factor by the first principal component of default rates and reproduce the estimations for systematic risk levels. Since the number of loans (cross-section) is much larger than the number of years (time-series), extracting the common factors through the principal component analysis could be problematic. We calculate the average default probability by state-year. We then extract the first principal component (PC1) from a panel of 52 states and 21 years. Before replicating the regression of the CPD model in Eq. (14) and estimating the systematic risk levels, we standardized the PC1 to allow for the magnitude comparison between Beta and AC. We summarize the results in Panel B of Table 11. The results are strongly consistent with our main finding regarding magnitudes and significance. The total systematic risk level across the three models is consistently at 7%, and Beta's influence becomes greater when more observed factors are incorporated into the model.

### 5.5.3. Risk-class estimations

Our final robustness test is to estimate the systematic risk level for different risk classes. Note that the risk classes are defined based on each individual loan's average default probabilities. We ensure that the number of default events is comparable between risk classes, so the default rates converge to conditional default probabilities. Hence, the first class has the most observations and the lowest default rate, while the last class has the least observations with the highest default rate.

<Insert Table 12 here>

We find that Beta estimates are not statistically significant throughout the classes in the TTC model, leaving AC as the sole contributor to the total systematic risk. In the limited PIT model, the contributions of Beta and AC are mostly comparable, but the driving force of AC tends to be stronger than Beta for higher-risk mortgages. As risk profiles for these mortgages could be entangled with multiple factors, the narrow involvement of observed systematic risk factors in the limited PIT could not help to capture the exposure. Therefore, AC likely overperforms Beta with this model. Regarding the comprehensive PIT model, Beta probably outweighs AC in forming total systematic risk. However, systematic risk is mainly driven by the frailty factor in the two lowest-risk classes, implying that low-risk mortgages are unlikely to suffer the adverse effects from macroeconomic risks but rather driven by the frailty factors.

We further notice that Beta and AC likely increase from the lowest to the highest-risk class, indicating that higher-risk mortgages have greater exposure to systematic risk factors than lower-risk mortgages. In the comprehensive PIT model, for example, Beta estimates rise from 0% to nearly 12%, and AC estimates rise from 0.7% to roughly 4%. Higher-risk mortgages are more exposed to systematic risk factors than lower-risk mortgages. This finding is strongly consistent to Hilscher & Wilson (2017).

Calem & Follain (2003) suggest the application of 15% for systematic risk levels in mortgages on single-family residencies which Basel regulations have adopted. Our analysis indicates that it may be more reasonable to use lower and different systematic risk levels for various mortgages based on their distinctive levels of risk. Consequently, a more suitable capital level may be derived to absorb potential future loan losses.

## 6. Industry impact

This research paper develops a unifying framework to measure the exposure levels to systematic risk for mortgages. The empirical evidence indicates that mortgage defaults are exposed to both observed and unobserved (frailty) systematic risk factors. Observed factors are dominant in driving systematic risk levels. We find meaningful differences in the exposures to systematic risk factors across regions, lenders, and recourse types. The model allows for a greater level of control when implementing risk measures compared to the current situation of placing all risks under a single parameter.

We also provide evidence of a positive relationship between mortgage rates and systematic risk levels, suggesting that mortgages with higher systematic risk levels require a higher premium. The inclusion of systematic risk levels in pricing is documented, and parameters differ for observed and unobserved risk. Pricing against systematic risk levels may be refined following more precise measures. For regulators, our findings suggest accounting for different systematic risk exposures in the regulatory regime to strengthen the financial system's resilience.

This could entail potential changes for institutions within this industry. At the moment, there is likely a dearth of knowledge regarding the systematic risk for banks and non-bank lenders. This is reflected in how regulators do not consider varying levels of systematic risk in their regulations and guidelines (currently using a standard AC of 15%). Our research results can assist policymakers in minimizing and adapting to a higher granular level of risk, which could push banks to improve their risk measurement frameworks. Furthermore, non-bank lenders should be included in the Basel framework due to their increased vulnerability to this risk.

Hopefully, the fruits of our research will assist organizations in the banking industry reduce the risks of mortgage defaults and increase profitability and growth through more streamlined and efficient risk settings. This can indirectly increase the option of adopting more favorable conditions for less risky consumers through lowered interest rates and more targeted loan offerings. Future research may improve mortgage portfolio strategies to benefit both banks and consumers.

However, it should be noted that the results are explicitly related to securitized US mortgages and the credit risks that may be applicable to these loans. Loan providers based outside the US in other international markets may have characteristics that may not be reflective of our analysis. Further research may generalize our empirical findings.

## Reference


Amromin, G., & Paulson, A. L. (2009). Comparing patterns of default among prime and subprime mortgages. *Economic Perspectives*, *33*(2), 18–37.

Antinolfi, G., Brunetti, C., & Im, J. (2016). Mortgage Rates and Credit Risk: Evidence from Mortgage Pools. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2809367

Aubuchon, C. P., Bandyopadhyay, S., Hernández-Murillo, R., & Martinek, C. J. (2009). District fares better than nation as prime-mortgage problems escalate. *The Regional Economist*, 20–21. http://research.stlouisfed.org/publications/regional/09/07/dist_ovrvw.pdf

Azizpour, S., Giesecke, K., & Schwenkler, G. (2018). Exploring the sources of default clustering. *Journal of Financial Economics*, *129*(1), 154–183. https://doi.org/10.1016/j.jfineco.2018.04.008

Bai, J., Bali, T. G., & Wen, Q. (2019). Common risk factors in the cross-section of corporate bond returns. *Journal of Financial Economics*, *131*(3), 619–642. https://doi.org/10.1016/j.jfineco.2018.08.002

Benetton, M., Eckley, P., Garbarino, N., Kirwin, L., & Latsi, G. (2021). Capital requirements and mortgage pricing: Evidence from Basel II. *Journal of Financial Intermediation*, *48*. https://doi.org/10.1016/j.jfi.2020.100883

Bessembinder, H. (1992). Systematic risk, hedging pressure, and risk premiums in futures markets. *Review of Financial Studies*, *5*(4), 637–667. https://doi.org/10.1093/rfs/5.4.637

Calabrese, R., & Crook, J. (2020). Spatial contagion in mortgage defaults: A spatial dynamic survival model with time and space varying coefficients. *European Journal of Operational Research*, *287*(2), 749–761. https://doi.org/10.1016/j.ejor.2020.04.031

Calem, P. S., & Follain, J. R. (2003). The asset-correlation parameter in Basel II for mortgages on single-family residences. *Basel II White Paper 5, Board of Governors of the Federal Reserve System (U.S.)*.

Chan, S., Haughwout, A., Hayashi, A., & van der Klaauw, W. (2016). Determinants of mortgage default and consumer credit use: The effects of foreclosure laws and foreclosure delays. *Journal of Money, Credit and Banking*, *48*(2–3), 393–413. https://doi.org/10.1111/jmcb.12304

Cotter, J., Gabriel, S., & Roll, R. (2015). Can housing risk be diversified? A cautionary tale from the housing boom and bust. *Review of Financial Studies*, *28*(3), 913–936. https://doi.org/10.1093/rfs/hhu085

Crook, J., & Banasik, J. (2012). Forecasting and explaining aggregate consumer credit delinquency behaviour. *International Journal of Forecasting*, *28*(1), 145–160. https://doi.org/10.1016/j.ijforecast.2010.12.002

Das, S. R., Duffie, D., Kapadia, N., & Saita, L. (2007). *Common Failings : How Corporate Defaults Are Correlated*. *62*(1), 93–117. http://www.jstor.org/stable/4123457

Dell'Ariccia, G., Igan, D., & Laeven, L. (2012). Credit booms and lending standards: Evidence from the subprime mortgage market. *Journal of Money, Credit and Banking*, *44*(3).

Demyanyk, Y., & Loutskina, E. (2016). Mortgage companies and regulatory arbitrage. *Journal of Financial Economics*, *122*(2), 328–351. https://doi.org/10.1016/j.jfineco.2016.07.003

Dietsch, M., & Petey, J. (2004). Should SME exposures be treated as retail or corporate exposures? A comparative analysis of default probabilities and asset correlations in French and German SMEs. *Journal of Banking & Finance*, *28*(4), 773–788. https://doi.org/10.1016/j.jbankfin.2003.10.006

Duan, J.-C., & Wei, J. (2009). Systematic risk and the price structure of individual equity options. *Review of Financial Studies*, *22*(5), 1981–2006. https://doi.org/10.1093/rfs/hhn057

Duffie, D., Eckner, A., Horel, G., & Saita, L. (2009). Frailty correlated default. *Journal of Finance*, *64*(5), 2089–2123. https://doi.org/10.1111/j.1540-6261.2009.01495.x

Duffie, D., Saita, L., & Wang, K. (2007). Multi-period corporate default prediction with stochastic covariates. *Journal of Financial Economics*, *83*(3), 635–665. https://doi.org/10.1016/j.jfineco.2005.10.011

Elul, B. R., Souleles, N. S., Chomsisengphet, S., Glennon, D., Hunt, R., Elmer, P., & Seelig, S. (2010). What “ triggers ” mortgage default ? *The American Economic Review*, *100(2)*(May), 490–494. https://www.jstor.org/stable/27805045

Elul, R., & Tilson, S. (2016). *Owner occupancy fraud and mortgage performance*. https://www.fdic.gov/analysis/cfr/consumer/2016/documents/elul-paper.pdf

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1–22. https://doi.org/10.1016/j.jfineco.2014.10.010

FDIC. (2019). *Quarterly Banking Profile*. https://www.fdic.gov/analysis/quarterly-banking-profile/fdic-quarterly/2019-vol13-4/fdic-v13n4-3q2019.pdf

Ghent, A. C., & Kudlyak, M. (2011). Recourse and residential mortgage default: Evidence from US states. *Review of Financial Studies*, *24*(9), 3139–3186. https://doi.org/10.1093/rfs/hhr055

Goodstein, R., Hanouna, P., Ramirez, C. D., & Stahel, C. W. (2017). Contagion effects in strategic mortgage defaults. *Journal of Financial Intermediation*, *30*, 50–60. https://doi.org/10.1016/j.jfi.2016.10.001

Gupta, A. (2019). Foreclosure contagion and the neighborhood spillover effects of mortgage defaults. *Journal of Finance*, *74*(5), 2249–2301. https://doi.org/10.1111/jofi.12821

Hashimoto, T. (2009). Asset correlation for credit risk analysis - Empirical study of default data for Japanese companies. In *Bank of Japan Working Paper Series*. http://www.boj.or.jp/en/research/wps_rev/wps_2009/data/wp09e03.pdf

Hilscher, J., & Wilson, M. (2017). Credit ratings and credit risk: Is one measure enough? *Management Science*, *63*(10), 3414–3437. https://doi.org/10.1287/mnsc.2016.2514

Irani, R. M., Iyer, R., Meisenzahl, R. R., & Peydró, J.-L. (2021). The Rise of Shadow Banking: Evidence from Capital Regulation. *The Review of Financial Studies*, *34*(5), 2181–2235. https://doi.org/10.1093/rfs/hhaa106

Jiménez, G., & Mencía, J. (2009). Modelling the distribution of credit losses with observable and latent factors. *Journal of Empirical Finance*, *16*(2), 235–253. https://doi.org/10.1016/j.jempfin.2008.10.003

Justiniano, A., Primiceri, G. E., & Tambalotti, A. (2022). The mortgage rate conundrum. *Journal of Political Economy*, *130*(1), 121–156. https://doi.org/10.1086/717043

Kim, Y. S., Laufer, S. M., Pence, K., Stanton, R., & Wallace, N. (2018). Liquidity crises in the mortgage market. *Brookings Papers on Economic Activity*, *2018*(Spring), 347–428. https://doi.org/10.1353/eca.2018.0004

Koopman, S. J., Lucas, A., & Schwaab, B. (2012). Dynamic factor models with macro, frailty, and industry effects for U.S. Default counts: The credit crisis of 2008. *Journal of Business and Economic Statistics*, *30*(4), 521–532. https://doi.org/10.1080/07350015.2012.700859

Lando, D., & Nielsen, M. S. (2010). Correlation in corporate defaults: Contagion or conditional independence? *Journal of Financial Intermediation*, *19*(3), 355–372. https://doi.org/10.1016/j.jfi.2010.03.002

Lee, Y., Rösch, D., & Scheule, H. (2021). Systematic credit risk in securitised mortgage portfolios. *Journal of Banking & Finance*, *122*, 105996. https://doi.org/10.1016/j.jbankfin.2020.105996

Leow, M., & Crook, J. (2016). The stability of survival model parameter estimates for predicting the probability of default: Empirical evidence over the credit crisis. *European Journal of Operational Research*, *249*(2), 457–464. https://doi.org/10.1016/j.ejor.2014.09.005

Levitin, A. J., Lin, D., & Wachter, S. M. (2020). Mortgage risk premiums during the housing bubble. *Journal of Real Estate Finance and Economics*, *60*(4), 421–468. https://doi.org/10.1007/s11146-018-9682-z

Liu, W., Miu, P., Chang, Y., & Ozdemir, B. (2012). Information asymmetry and bank regulation: Can the spread of debt contracts be explained by recovery rates? *Journal of Financial Intermediation*, *21*(1), 123–150. https://doi.org/10.1016/j.jfi.2011.07.001

Mayer, C., Pence, K., & Sherlund, S. M. (2009). The rise in mortgage defaults. *Journal of Economic Perspectives*, *23*(1), 27–50. https://doi.org/10.1257/jep.23.1.27

Nguyen, D. D., Ongena, S., Qi, S., & Sila, V. (2022). Climate Change Risk and the Cost of Mortgage Credit. *Review of Finance*. https://doi.org/10.1093/rof/rfac013

Nickerson, J., & Griffin, J. M. (2017). Debt correlations in the wake of the financial crisis: What are appropriate default correlations for structured products? *Journal of Financial Economics*, *125*(3), 454–474. https://doi.org/10.1016/j.jfineco.2017.06.011

Pesaran, M. H., Schuermann, T., Treutler, B., & Weiner, S. M. (2006). Macroeconomic dynamics and credit risk: A global perspective. *Journal of Money, Credit and Banking*, *38*(5), 1211–1261. https://www.jstor.org/stable/3839005

Rajan, U., Seru, A., & Vig, V. (2015). The failure of models that predict failure: Distance, incentives, and defaults. *Journal of Financial Economics*, *115*(2), 237–260. https://doi.org/10.1016/j.jfineco.2014.09.012

Wang, H., Zhou, H., & Zhou, Y. (2013). Credit default swap spreads and variance risk premia. *Journal of Banking and Finance*, *37*(10), 3733–3746. https://doi.org/10.1016/j.jbankfin.2013.02.021

## Tables and Figures

### Table 1: Literature review

**Note:** This table summarizes the literature review on systematic risk. Stream 1 refers to studies estimating the impacts of systematic risk factors but do not estimate the systematic risk levels. Stream 2 refers to those estimating systematic risk levels explicitly.

| No | Paper | Region | Period | Model | Asset class | Observed syst.risk factor | Unobserved syst.risk factor | Stream |
|---|---|---|---|---|---|---|---|---|
| 1 | Our paper | US | 1999 – 2019 | Nonlinear mixed model | Mortgage | Yes | Yes | 2 |
| 2 | Lee et al. (2021) | US | 2002 - 2014 | State space | Mortgage | No | Yes | 2 |
| 3 | Calem and Follain (2003) | US | 1982 – 2000 | Survival model | Mortgage | No | Yes | 2 |
| 4 | Gupta (2019) | US | 2000 - 2010 | IV regression | Mortgage | Yes | No | 1 |
| 5 | Goodstein et al. (2017) | US | 2005 - 2009 | Logit | Mortgage | Yes | No | 1 |
| 6 | Amromin and Paulson (2009) | US | 2004 - 2007 | Probit | Mortgage | Yes | No | 1 |
| 7 | Elul et al. (2010) | US | 2005 - 2009 | Logit | Mortgage | Yes | No | 1 |
| 8 | Calabrese and Crook (2020) | UK | 2006 - 2015 | Spatial generalised extreme value survival model | Mortgage | Yes | No | 1 |
| 9 | Leow and Crook (2016) | UK | 2002 - 2011 | Logit | Mortgage | Yes | No | 1 |
| 10 | Crook and Banasik (2012) | US | 1988 - 2008 | Error correction | Consumer credit and mortgage | Yes | No | 1 |
| 11 | Hashimoto (2009) | Japan | 1985 to 2005 | Ordered probit model | Corporate | No | Yes | 2 |
| 12 | Jiménez and Mencía (2009) | Spain | 1984 - 2006 | Vector autoregression (VAR) | Corporate | Yes | Yes | 1 |
| 13 | Azizpour et al. (2018) | US | 1970 -2012 | Method of maximum likelihood | Corporate | Yes | Yes | 1 |
| 14 | Hilscher and Wilson (2017) | US | 1986 – 2013 | Dynamic logit model for Failure score OLS for failure Beta | Corporate | Yes | No | 2 |
| 15 | Nickerson and Griffin (2017) | US | 2000 - 2007 | Joint model estimated by MLE | Corporate | Yes | Yes | 1 |
| 16 | Duffie et al. (2009) | US | 1979 - 2004 | Autoregressive Gaussian time-series model | Corporate | No | Yes | 1 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 17 | Dietsch and Petey (2004) | France and Germany | 1995 – 2001 (France) 1997 – 2001 (Germany) | Probit ordered model | Corporate | No | Yes | 1 |
| 18 | Koopman et al. (2012) | US | 1981 - 2005 | Logit | Corporate | Yes | Yes | 1 |
| 19 | Duffie et al. (2007) | US | 1980 - 2004 | Double stochastic model with joint MLE | Corporate | Yes | No | 1 |
| 20 | Das et al. (2007) | US | 1979 - 2004 | Doubly stochastic model | Corporate | Yes | No | 1 |
| 21 | Pesaran et al. (2006) | US | 1987 - 2003 | Global vector autoregressive macroeconomic model | Corporate | Yes | No | 1 |

## Table 2: Variable definitions

**Note:** This table presents the variable definitions used in our paper. The data source for indicator variables, borrower characteristics, and loan characteristics is Federal Housing Finance Agency. Unemployment rate (UER) and HPI are sourced from the FRED database provided by the St. Louis Federal Reserve Bank.

| Variable | Description |
|---|---|
| $D_{it}$ | Default indicator equals to 1 if loans have been delinquent for 90 days or more, have been acquired by REO acquisition or REO disposition, or have been involved in short sale or charge off and zero otherwise |
| $P_{it}$ | Payoff indicator equals to 1 if a loan balance becomes zero due to the prepaid, matured or repurchase prior to property disposition and zero otherwise |
| FICO | Borrower's credit score created by Fair Isaac Corporation |
| Orig LTV | Ratio between original mortgage loan amount and house value |
| Orig DTI | Ratio between borrower's monthly debt payment and total monthly income at the origination time |
| Refinancing | Dummy variable receives value of 1 if mortgage is either cash-out or no cash-out refinanced and zero otherwise |
| Multiple | Dummy variable receives value of 1 if there are more than one borrower obligated to repay loan and zero otherwise |
| SF | Dummy variable receives value of 1 if property type secured by the mortgage is single-family home and zero otherwise |
| TPO | Dummy variable receives value of 1 if mortgage was originated or involved in the third-party organization such as a broker or a correspondent and zero otherwise |
| MI | Dummy variable receives value of 1 if borrower is required to obtain a mortgage insurance and zero otherwise |
| PP | Estimated payoff probability |
| LTV_change | Difference between current LTV and Orig LTV<br>Current LTV estimated with annual data is ratio of current loan balance and house value. We estimate current house value based on the HPI at zip code level as the product of original house value and ratio of current HPI and original HPI. |
| Loan age | Time between current year and origination year |
| Loan age$^2$ | Square of loan age |
| HPI_change | Percentage change of national HPI in year t as compared to year t-1 |
| UER_change | Percentage change of national unemployment rate in year t as compared to year t-1 |

**Table 3: Mortgage performance by categorical variables**

Note: This table describes the mortgage data at the annual level. The loan purpose indicates whether a mortgage is a house purchase or loan refinance. The number of borrowers indicates whether a mortgage has one or more than one borrower. SF loans variable indicates whether the property type secured for the mortgage is a single-family home. Channel shows whether mortgages originated by a retail lender or associated with a third-party organization. Mortgage insurance shows whether mortgage insurance is required. Current year is the observation year. Origination year is the year when a mortgage is originated.

**Note:**

| **Loan features** | | **No of Obs** | **No of default events** | **Default rate (%)** | **No of payoff events** | **Payoff rate (%)** |
|---|---|---|---|---|---|---|
| Loan purpose | | | | | | |
| | Purchase | 43,036,162 | 405,235 | 0.942% | 6,288,710 | 14.613% |
| | Refinancing | 57,601,686 | 670,349 | 1.164% | 8,245,742 | 14.315% |
| Number borrowers | | | | | | |
| | One | 45,168,500 | 625,638 | 1.385% | 11,045,786 | 14.510% |
| | Multiple | 55,469,348 | 449,946 | 0.811% | 3,488,666 | 14.231% |
| SF loans | | | | | | |
| | Yes | 76,123,640 | 852,241 | 1.120% | 11,045,786 | 14.510% |
| | No | 24,514,208 | 223,343 | 0.911% | 3,488,666 | 14.231% |
| Channel | | | | | | |
| | Retail | 47,162,282 | 401,645 | 0.852% | 6,611,743 | 14.019% |
| | Third Party Organization | 53,475,566 | 673,939 | 1.260% | 7,922,709 | 14.816% |
| Mortgage insurance | | | | | | |
| | Yes | 24,082,880 | 371,277 | 1.542% | 3,344,278 | 13.887% |
| | No | 76,554,968 | 704,307 | 0.920% | 11,190,174 | 14.617% |
| Current year | | | | | | |
| | 1999-2001 | 5,453,769 | 25,542 | 0.468% | 640,974 | 11.753% |
| | 2002-2004 | 13,112,030 | 94,829 | 0.723% | 3,332,001 | 25.412% |
| | 2005-2007 | 15,018,287 | 107,900 | 0.718% | 1,487,388 | 9.904% |
| | 2008-2010 | 18,941,112 | 438,903 | 2.317% | 2,595,133 | 13.701% |
| | 2011-2013 | 15,850,737 | 245,030 | 1.546% | 3,058,410 | 19.295% |
| | 2014-2016 | 14,877,321 | 83,195 | 0.559% | 1,716,325 | 11.537% |
| | 2017-2019 | 17,384,592 | 80,185 | 0.461% | 1,704,221 | 9.803% |
| Origination year | | | | | | |
| | 1999-2001 | 12,548,238 | 126,434 | 1.008% | 2,988,301 | 23.815% |
| | 2002-2004 | 26,691,452 | 253,843 | 0.951% | 4,035,595 | 15.119% |
| | 2005-2007 | 19,007,701 | 463,158 | 2.437% | 2,542,449 | 13.376% |
| | 2008-2010 | 15,675,743 | 161,879 | 1.033% | 2,523,562 | 16.099% |
| | 2011-2013 | 11,239,249 | 22,093 | 0.197% | 1,054,863 | 9.386% |
| | 2014-2016 | 10,662,843 | 33,246 | 0.312% | 978,982 | 9.181% |
| | 2017-2019 | 4,812,622 | 14,931 | 0.310% | 410,700 | 8.534% |
| | **All** | **100,637,848** | **1,075,584** | **1.069%** | **14,534,452** | **14.442%** |

## Table 4: Descriptive Statistics

**Note:** This table shows the descriptive statistics of metric variables for the full sample, default loans, and payoff loans. The definitions of all the below variables are presented in Table 2.

| | **Full sample** | | | | **Default loans** | | **Payoff loans** | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Error | Min | Max | Mean | Std. Error | Mean | Std. Error |
| FICO | 731.734 | 54.866 | 300.000 | 850.000 | 684.547 | 56.182 | 731.750 | 53.953 |
| Orig LTV | 0.736 | 0.162 | 0.060 | 1.050 | 0.790 | 0.132 | 0.732 | 0.162 |
| Orig DTI | 0.341 | 0.112 | 0.010 | 0.650 | 0.388 | 0.110 | 0.341 | 0.113 |
| LTV_change | -0.098 | 0.144 | -0.627 | 0.299 | -0.006 | 0.177 | -0.236 | 0.169 |
| Loan age (Years) | 3.181 | 3.156 | 0.000 | 20.792 | 4.139 | 2.958 | 3.452 | 2.969 |
| HPI_change | 0.024 | 0.052 | -0.074 | 0.114 | -0.008 | 0.056 | 0.022 | 0.051 |
| UER_change | 0.014 | 0.193 | -0.163 | 0.601 | 0.100 | 0.257 | 0.028 | 0.195 |

## Table 5: Estimation of payoff probability (Stage 1)

**Note:** This table presents the payoff probability (PP) estimate. The TTC model for PP is specified in Equation (3). The limited PIT model for PP is specified in Equation (4). The comprehensive PIT model for PP is specified in Equation (5). The dependent variable in all four models is the payoff indicator. Dummies for origination years and states are skipped for simplicity. Standard errors are in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% confidence levels respectively. The fit statistics include the value of area under the curve (AUROC), rescaled R-square. The number of observations is also provided.

| | TTC | Limited PIT | Comprehensive PIT |
|---|---|---|---|
| Intercept | -1.775***<br>(0.003) | -1.413***<br>(0.003) | -1.151***<br>(0.003) |
| FICO | 0.083***<br>(0) | 0.024***<br>(0) | 0.016***<br>(0) |
| Orig LTV | -0.001<br>(0.001) | -1.112***<br>(0.002) | -1.135***<br>(0.002) |
| Orig DTI | 0.043***<br>(0.001) | 0.296***<br>(0.002) | 0.318***<br>(0.002) |
| Refinancing | -0.05***<br>(0) | 0.035***<br>(0) | 0.039***<br>(0) |
| Multiple borrowers | 0.089***<br>(0) | 0.107***<br>(0) | 0.105***<br>(0) |
| Property types | 0.05***<br>(0) | 0.022***<br>(0) | 0.02***<br>(0) |
| Third-party origination | 0.017***<br>(0) | 0.027***<br>(0) | 0.027***<br>(0) |
| Mortgage insurance | -0.029***<br>(0) | -0.022***<br>(0.001) | -0.023***<br>(0.001) |
| LTV_change | | -6.654***<br>(0.003) | -6.913***<br>(0.003) |
| Loan age | | -0.023***<br>(0) | -0.068***<br>(0) |
| Loan age$^2$ | | -0.007***<br>(0) | -0.006***<br>(0) |
| HPI_change | | | -4.768***<br>(0.006) |
| UER_change | | | -1.06***<br>(0.002) |
| Vintage dummies | No | Yes | Yes |
| State dummies | Yes | Yes | Yes |
| AUROC | 0.549 | 0.862 | 0.869 |
| Max-rescaled R-square | 0.007 | 0.368 | 0.378 |
| No of obs | 99,151,998 | 99,151,998 | 99,151,998 |

**Table 6: Estimation of default probability (Stage 2)**

**Note:** This table presents the PD estimate. The TTC model for PD is specified in Equation (8). The limited PIT model for PD is specified in Equation (9). The comprehensive PIT model for PD is specified in Equation (10). The dependent variable in all models is the default indicator defined in Table 2. Dummies for origination years and states are skipped for simplicity. Standard errors are in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% confidence levels respectively. The fit statistics include the value of area under the curve (AUROC), rescaled R-square. The number of observations is also provided.

| | TTC | Limited PIT | Comprehensive PIT |
|---|---|---|---|
| Intercept | -0.553***<br>(0.007) | -0.730***<br>(0.007) | -0.590***<br>(0.007) |
| FICO | -0.366***<br>(0) | -0.416***<br>(0) | -0.428***<br>(0) |
| Orig LTV | 0.978***<br>(0.004) | 1.031***<br>(0.005) | 1.035***<br>(0.005) |
| Orig DTI | 0.747***<br>(0.004) | 0.697***<br>(0.004) | 0.71***<br>(0.004) |
| Refinancing | 0.113***<br>(0.001) | 0.119***<br>(0.001) | 0.123***<br>(0.001) |
| Multiple borrowers | -0.15***<br>(0.002) | -0.21***<br>(0.001) | -0.215***<br>(0.001) |
| Property types (SF) | -0.002<br>(0.001) | -0.034***<br>(0.001) | -0.036***<br>(0.001) |
| Third-party origination | 0.071***<br>(0.001) | 0.064***<br>(0.001) | 0.065***<br>(0.001) |
| Mortgage insurance | 0.01***<br>(0.001) | 0.04***<br>(0.001) | 0.046***<br>(0.001) |
| Payoff probability | -2.988***<br>(0.075) | -0.186***<br>(0.006) | -0.169***<br>(0.006) |
| Change in LTV | | 1.294***<br>(0.006) | 1.276***<br>(0.006) |
| Loan age | | 0.162***<br>(0.001) | 0.14***<br>(0.001) |
| Loan age$^2$ | | -0.011***<br>(0) | -0.008***<br>(0) |
| Change in HPI | | | -1.845***<br>(0.014) |
| UER change | | | 0.232***<br>(0.003) |
| Vintage dummies | No | Yes | Yes |
| State dummies | Yes | Yes | Yes |
| AUROC | 0.778 | 0.844 | 0.845 |
| Max-rescaled R-square | 0.097 | 0.162 | 0.169 |
| Number of observations | 99,151,998 | 99,151,998 | 99,151,998 |

**Table 7: Estimates of CPD model (Stage 3)**

**Note:** Panel A of this table presents the estimation results of the conditional PD model specified in Equation (14). The dependent variable is the annual default rate. The independent variable includes observed and unobserved systematic risk factors. Panel B of this table presents the estimates of Beta and AC as specified in Equation (16). The total systematic risk level is the sum of Beta and AC. Beta's contribution is the ratio of Beta to total systematic risk, and AC's contribution is the ratio of AC to total systematic risk. Default variance represents the default clustering or observable systematic risk. Total S.Risk explanation shows the ratio between total systematic risk and default variance to show how the estimated systematic risk has explained much default variance. The name of the model is consistent with the PD models, including the TTC model specified in Equation (8), the Limited PIT model specified in Equation (9), and the comprehensive PIT model specified in Equation (10). Standard errors are in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% confidence levels respectively.

| | **TTC model** | **Limited PIT** | **Comprehensive PIT** |
|---|---|---|---|
| ***Panel A: CPD equation*** | | | |
| a | -2.423***<br>(0.058) | -2.409***<br>(0.035) | -2.398***<br>(0.03) |
| b | -0.011<br>(0.056) | 0.222***<br>(0.038) | 0.246***<br>(0.033) |
| c | 0.261***<br>(0.04) | 0.161***<br>(0.025) | 0.138***<br>(0.021) |
| ***Panel B: Systematic risk levels*** | | | |
| Beta | 0<br>(0.001) | 0.046***<br>(0.015) | 0.056***<br>(0.014) |
| AC | 0.064***<br>(0.018) | 0.024***<br>(0.007) | 0.018***<br>(0.005) |
| Total systematic risk | 0.064***<br>(0.019) | 0.07***<br>(0.016) | 0.074***<br>(0.015) |
| Beta's contribution | 0 | 66% | 76% |
| AC's contribution | 100% | 34% | 24% |
| Default variance | 0.103 | 0.103 | 0.103 |
| Total S.Risk explanation | 62% | 68% | 72% |

**Table 8: Systematic risk levels for sub-samples (Stage 3)**

**Note:** This table presents the estimates of Beta and AC for different types of lenders (banks vs. nonbank lenders) in Panel A, for different types of the judicial system (recourse vs. non-recourse states) in Panel B, and for different states (CA vs other states). Non-recourse states include AK, AZ, CA, CT, ID, MN, NC, ND, OR, TX, UT, and WA. Other states follow the recourse rule. Beta and AC are estimated as specified in Eq. (18) and Eq. (19) for each sub-sample. The dependent variable is the default rate by year of each sub-sample. The independent variables are observed and unobserved systematic risk factors. Each model uses the standardized Mean PD from the corresponding PD model as the proxy of observed systematic risk factor. Unobserved factors are proxied by a set of time (year) dummies. Standard errors are in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% confidence levels respectively. All results are expressed in percentages.

| | | | | | | |
|---|---|---|---|---|---|---|
| **Panel A: Banks vs. Nonbank institutions** | | | | | | |
| | TTC model | Limited PIT | Comp. PIT | TTC model | Limited PIT | Comp. PIT |
| | Beta | | | AC | | |
| Bank | 3.122* | 5.309*** | 5.446*** | 4.364*** | 2.623*** | 1.406*** |
| | (0.017) | (0.017) | (0.013) | (0.013) | (0.008) | (0.004) |
| Nonbank | 3.427** | 5.145*** | 5.188*** | 3.735*** | 2.433*** | 2.444*** |
| | (0.016) | (0.016) | (0.016) | (0.011) | (0.007) | (0.007) |
| **Panel B: Recourse states vs. Non-recourse states** | | | | | | |
| | TTC model | Limited PIT | Comp. PIT | TTC model | Limited PIT | Comp. PIT |
| | Beta | | | AC | | |
| Recourse | 2.831* | 4.198*** | 4.897*** | 3.334*** | 2.123*** | 1.987*** |
| | (0.014) | (0.013) | (0.014) | (0.01) | (0.006) | (0.006) |
| Non-recourse | 3.329* | 5.359*** | 6.364*** | 4.7*** | 2.906*** | 2.087*** |
| | (0.018) | (0.018) | (0.016) | (0.014) | (0.009) | (0.006) |
| **Panel C: California vs. Other states** | | | | | | |
| | TTC model | Limited PIT | Comp. PIT | TTC model | Limited PIT | Comp. PIT |
| | Beta | | | AC | | |
| California | 7.262** | 9.441*** | 11.439*** | 8.126*** | 5.337*** | 1.213*** |
| | (0.034) | (0.03) | (0.016) | (0.023) | (0.016) | (0.004) |
| Other states | 3.149** | 4.135*** | 4.701*** | 3.408*** | 2.078*** | 2.109*** |
| | (0.015) | (0.013) | (0.014) | (0.01) | (0.006) | (0.006) |

## Table 9: Pricing results on full sample (Stage 4)

**Note:** This table presents the impact of exposure to systematic risk on the mortgage interest rate. The exposure is computed as the unexpected loss (UL) as the difference between the VaR and unconditional PD. As specified in Basel III, VaR is calculated from the estimated systematic risk levels (Beta or AC), PD, and conservative systematic risk value (0.999). The names of the columns correspond to the PD models, which are the TTC model specified in Eq. (8), the limited PIT model specified in Eq. (9), and the comprehensive PIT model specified in Eq. (10). Rate is the national average rate on 30-year fixed-rate mortgages. We include all loans and borrowers' characteristics, including FICO, DTI, LTV, original loan size, dummies for single-family property, refinancing loans, multiple borrowers, third-party originations, and mortgage insurance as control variables. State dummies are also included. Standard errors are clustered by lenders to control for standard lending differences and are reported in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% confidence levels respectively. We also provide the R-square and number of observations for each pricing regression at the bottom of the table.

| | **Regulatory value** | **TTC** | **Limited PIT** | **Comp. PIT** |
|---|---|---|---|---|
| $UL_{Beta}$ | | 0.0034<br>(0.005) | 0.0318***<br>(0.003) | 0.045***<br>(0.006) |
| $UL_{AC}$ | | 0.0196***<br>(0.005) | 0.0162**<br>(0.008) | 0.0003<br>(0.004) |
| $UL_{15\%}$ | 0.015***<br>(0.003) | | | |
| Rate | 0.8693***<br>(0) | 0.8694***<br>(0) | 0.8568***<br>(0) | 0.8581***<br>(0) |
| Intercept | 0.0282***<br>(0.002) | 0.0313***<br>(0.002) | 0.0316***<br>(0.002) | 0.0309***<br>(0.001) |
| Control variables | Yes | Yes | Yes | Yes |
| Lender and state dummies | Yes | Yes | Yes | Yes |
| R-square | 88.10 | 88.09 | 88.14 | 88.19 |
| No of obs | 18,050,132 | 18,050,132 | 18,050,132 | 18,050,132 |

**Table 10: Pricing results for sub-samples (Stage 4)**

**Note:** This table presents the impact of exposure to systematic risk on the mortgage interest rate for different sub-samples. The exposure is computed as the unexpected loss (UL) as the difference between the VaR and unconditional PD. VaR is calculated from the estimated systematic risk levels (Beta or AC), PD and conservative systematic risk value (0.999) as specified in Basel III. The names of the columns correspond to the PD models, which are the TTC model specified in Eq. (8), the limited PIT model specified in Eq. (9), and the comprehensive PIT model specified in Eq. (10). Rate is the national average rate on 30-year fixed-rate mortgages. We include all loans and borrowers' characteristics, including FICO, DTI, LTV, original loan size, dummies for single-family property, refinancing loans, multiple borrowers, third-party originations, and mortgage insurance as control variables. State dummies are also included. Panel A shows the pricing results for banks and nonbank lenders. Panel B shows the pricing results for recourse and non-recourse states. Panel C shows the pricing results for California and other states. Standard errors are clustered by the lender to control for lending standards and are reported in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% confidence levels respectively. We also provide the R-square and number of observations for each pricing regression at the bottom of each panel.

| **Panel A** | **Banks** | | | **Nonbank lenders** | | |
|---|---|---|---|---|---|---|
| | TTC | Limited PIT | Comp. PIT | TTC | Limited PIT | Comp. PIT |
| $UL_{Beta}$ | 0.0085*** | 0.0231*** | 0.0417*** | 0.0148*** | 0.028*** | 0.038*** |
| | (0.003) | (0.004) | (0.007) | (0.005) | (0.005) | (0.008) |
| $UL_{AC}$ | 0.0095*** | 0.024*** | 0.0073** | 0.016*** | 0.0172** | 0.0056 |
| | (0.003) | (0.005) | (0.003) | (0.005) | (0.008) | (0.005) |
| Rate | 0.8606*** | 0.8484*** | 0.8491*** | 0.8734*** | 0.8624*** | 0.8637*** |
| | (0.016) | (0.018) | (0.018) | (0.011) | (0.011) | (0.012) |
| Intercept | 0.0331*** | 0.0322*** | 0.0312*** | 0.0311*** | 0.0317*** | 0.0313*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Control variable | Yes | Yes | Yes | Yes | Yes | Yes |
| Seller cluster | Yes | Yes | Yes | Yes | Yes | Yes |
| State dummy | Yes | Yes | Yes | Yes | Yes | Yes |
| R-square | 87.09 | 87.14 | 87.23 | 88.72 | 88.75 | 88.79 |
| No of obs | 7,827,193 | 7,827,193 | 7,827,193 | 10,222,939 | 10,222,939 | 10,222,939 |
| **Panel B** | **Recourse states** | | | **Non-recourse states** | | |
| | TTC | Limited PIT | Comp. PIT | TTC | Limited PIT | Comp. PIT |
| $UL_{Beta}$ | 0.0126*** | 0.0296*** | 0.0453*** | 0.0108*** | 0.0224*** | 0.0328*** |
| | (0.004) | (0.004) | (0.007) | (0.003) | (0.003) | (0.005) |
| $UL_{AC}$ | 0.0161*** | 0.0199*** | 0.0044 | 0.0119*** | 0.0198*** | 0.0109*** |
| | (0.005) | (0.007) | (0.004) | (0.003) | (0.004) | (0.003) |
| Rate | 0.8799*** | 0.8681*** | 0.8692*** | 0.8524*** | 0.8411*** | 0.8422*** |
| | (0.011) | (0.012) | (0.012) | (0.008) | (0.009) | (0.009) |
| Intercept | 0.0316*** | 0.0316*** | 0.0308*** | 0.0326*** | 0.0326*** | 0.0322*** |
| | (0.002) | (0.002) | (0.002) | (0.001) | (0.001) | (0.001) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Control variable | Yes | Yes | Yes | Yes | Yes | Yes |
| Seller cluster | Yes | Yes | Yes | Yes | Yes | Yes |
| State dummy | Yes | Yes | Yes | Yes | Yes | Yes |
| R-square | 87.79 | 87.83 | 87.90 | 88.56 | 88.60 | 88.65 |
| No of obs | 11,502,573 | 11,502,573 | 11,502,573 | 6,547,559 | 6,547,559 | 6,547,559 |

| **Panel C** | | **CA** | | | **Other states** | |
|---|---|---|---|---|---|---|
| | TTC | Limited PIT | Comp. PIT | TTC | Limited PIT | Comp. PIT |
| $UL_{Beta}$ | 0.0034*** | 0.0061*** | 0.0077*** | 0.0147*** | 0.0337*** | 0.042*** |
| | (0.001) | (0.001) | (0.001) | (0.004) | (0.004) | (0.006) |
| $UL_{AC}$ | 0.0043*** | 0.007*** | 0.0086*** | 0.0165*** | 0.0185** | 0.0102** |
| | (0.001) | (0.002) | (0.002) | (0.005) | (0.008) | (0.005) |
| Mortgage30US | 0.8513*** | 0.846*** | 0.8469*** | 0.8728*** | 0.8601*** | 0.8626*** |
| | (0.008) | (0.008) | (0.008) | (0.011) | (0.011) | (0.011) |
| Intercept | 0.0297*** | 0.0301*** | 0.0301*** | 0.0322*** | 0.0322*** | 0.0320*** |
| | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) |
| Control variable | Yes | Yes | Yes | Yes | Yes | Yes |
| Seller cluster | Yes | Yes | Yes | Yes | Yes | Yes |
| State dummy | Yes | Yes | Yes | Yes | Yes | Yes |
| R-square | 88.94 | 88.94 | 88.95 | 87.92 | 87.97 | 88.02 |
| No of obs | 2,353,651 | 2,353,651 | 2,353,651 | 15,696,481 | 15,696,481 | 15,696,481 |

**Table 11: Robustness tests – Systematic risk level using different proxies**

**Note:** This table shows the results from robustness tests when changing the default indicator and the proxy of observed factors. Panel A shows the estimates of Beta, AC, and total systematic risk levels when the default indicator is defined as either being delinquent for at least 60 days or being involved in foreclosure events. Panel B shows the estimates when the first principal component obtained from the state-year PD panel is used as the proxy for the observed systematic risk factor. Beta's (AC's) contribution is the ratio between Beta (AC) and the total systematic risk level. Standard errors are reported in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% confidence levels respectively.

**Panel A: Different default indicator**

| | TTC | Limited PIT | Comprehensive PIT |
|---|---|---|---|
| Beta | 0.0165* | 0.0312*** | 0.0351*** |
| | (0.009) | (0.009) | (0.009) |
| AC | 0.0258*** | 0.0136*** | 0.0117*** |
| | (0.008) | (0.004) | (0.004) |
| Total systematic risk | 0.0423*** | 0.0449*** | 0.0468*** |
| | (0.012) | (0.01) | (0.01) |
| Beta's contribution | 39% | 70% | 75% |
| AC's contribution | 61% | 30% | 25% |

**Panel B: The first principal component as the proxy for observed factor**

| | TTC | Limited PIT | Comprehensive PIT |
|---|---|---|---|
| | 0.0295* | 0.0456*** | 0.0512*** |
| Beta | (0.015) | (0.015) | (0.015) |
| | 0.0375*** | 0.0238*** | 0.0203*** |
| AC | (0.011) | (0.007) | (0.006) |
| | 0.067*** | 0.0694*** | 0.0715*** |
| Total systematic risk | (0.018) | (0.016) | (0.016) |
| Beta's contribution | 44% | 66% | 72% |
| AC's contribution | 56% | 34% | 28% |

**Table 12: Robustness test - Systematic risk levels across risk classes**

**Note:** This table presents the estimates of Beta and AC for different risk classes. Risk classes are categorized based on average PD per loan, and the number of default events in each class is ensured to be comparable. The lowest risk class consists of mortgages with the lowest PD. The highest risk class consists of mortgages with the highest PD. Beta and AC are estimated as specified in Eq. (18) and Eq. (19) for each risk class. The dependent variable is the default rate by year of each risk class. The independent variables are observed and unobserved systematic risk factors. Each model uses the standardized Mean PD from the corresponding PD model to proxy for observed systematic risk factors. Unobserved factors are proxied by the set of time (year) dummies. Standard errors are in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% confidence levels respectively.

| | **TTC** | **Limited PIT** | **Comp. PIT** | **TTC** | **Limited PIT** | **Comp. PIT** |
|---|---|---|---|---|---|---|
| | Beta | | | AC | | |
| Lowest-risk class | 1.532 | 0.103 | 0.023 | 3.608*** | 0.593*** | 0.619*** |
| | (0.01) | (0.001) | (0.001) | (0.011) | (0.002) | (0.002) |
| 2nd class | 1.46 | 0.768* | 0.236 | 6.107*** | 1.003*** | 0.402*** |
| | (0.013) | (0.004) | (0.001) | (0.019) | (0.003) | (0.001) |
| 3rd class | 1.184 | 1.477* | 0.721*** | 6.888*** | 1.583*** | 0.035*** |
| | (0.012) | (0.007) | (0.001) | (0.021) | (0.005) | (0) |
| 4th class | 0.949 | 2.006** | 1.557*** | 7.239*** | 2.158*** | 0.113*** |
| | (0.011) | (0.01) | (0.002) | (0.022) | (0.007) | (0) |
| 5th class | 0.722 | 2.32* | 2.456*** | 7.625*** | 2.988*** | 0.574*** |
| | (0.01) | (0.012) | (0.006) | (0.023) | (0.009) | (0.002) |
| 6th class | 0.528 | 2.578 | 3.43*** | 7.798*** | 4.352*** | 1.291*** |
| | (0.009) | (0.015) | (0.01) | (0.024) | (0.013) | (0.004) |
| 7th class | 0.269 | 3.094 | 4.305*** | 8.344*** | 5.655*** | 2.105*** |
| | (0.006) | (0.019) | (0.014) | (0.025) | (0.017) | (0.006) |
| 8th class | 0.097 | 4.001 | 5.515*** | 8.814*** | 7.088*** | 2.99*** |
| | (0.004) | (0.024) | (0.018) | (0.026) | (0.021) | (0.009) |
| 9th class | 0.004 | 5.693* | 7.442*** | 9.824*** | 8.882*** | 3.919*** |
| | (0.001) | (0.032) | (0.024) | (0.029) | (0.026) | (0.011) |
| Highest-risk class | 0.737 | 8.925* | 11.648*** | 11.773*** | 12.868*** | 3.297*** |
| | (0.012) | (0.046) | (0.026) | (0.034) | (0.036) | (0.01) |

**Figure 1: Default rate and Mean PD**

**Note:** This figure shows the fluctuations of default rate (solid line) and Mean PD (dash line) over time for three different PD models, including the TTC model specified in Eq. (8), the limited PIT model specified in Eq. (9), and the comprehensive PIT model specified in Eq. (10). The shaded areas indicate the recession periods as defined by NBER. The mean deviation between the observed default rate and estimated PD is 0.4% for the TTC model, 0.3% for the limited PIT model, and 0.2% for the comprehensive PIT model.

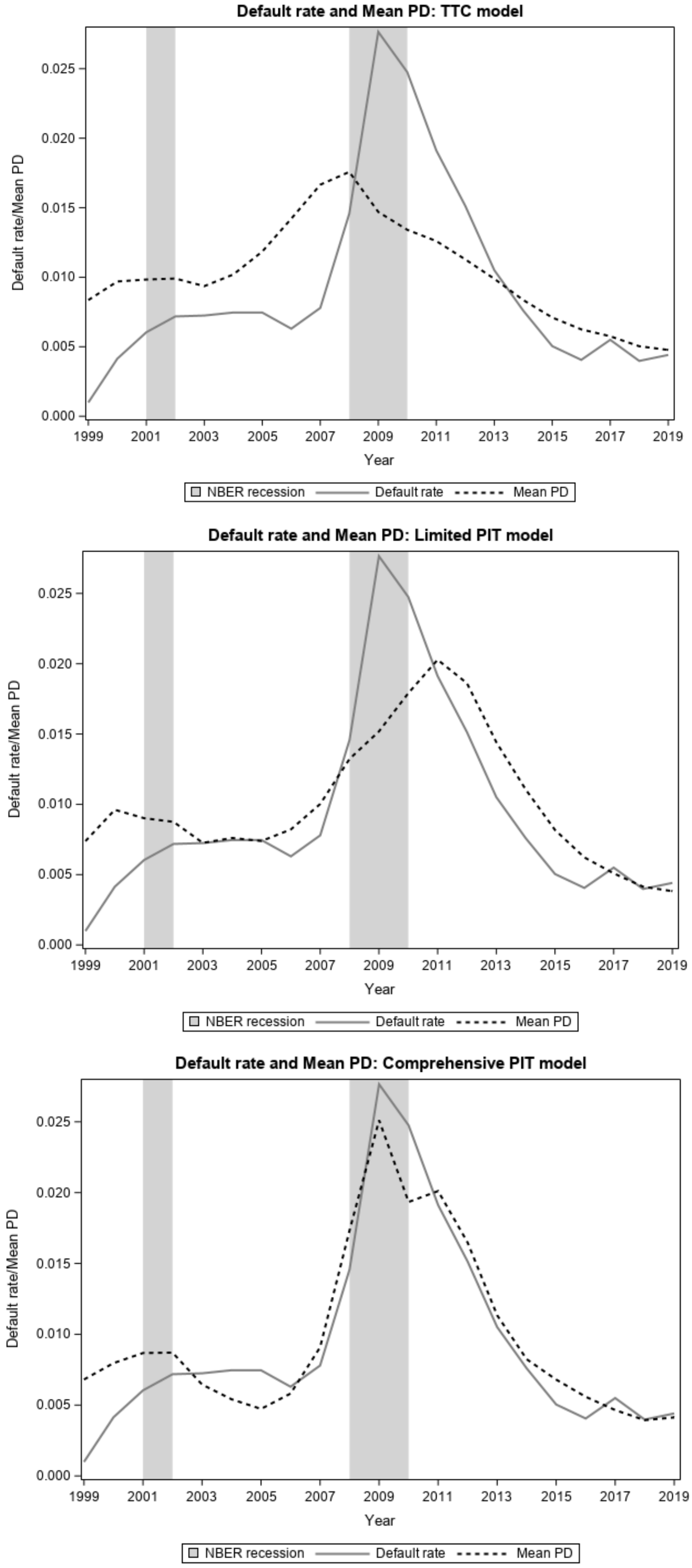
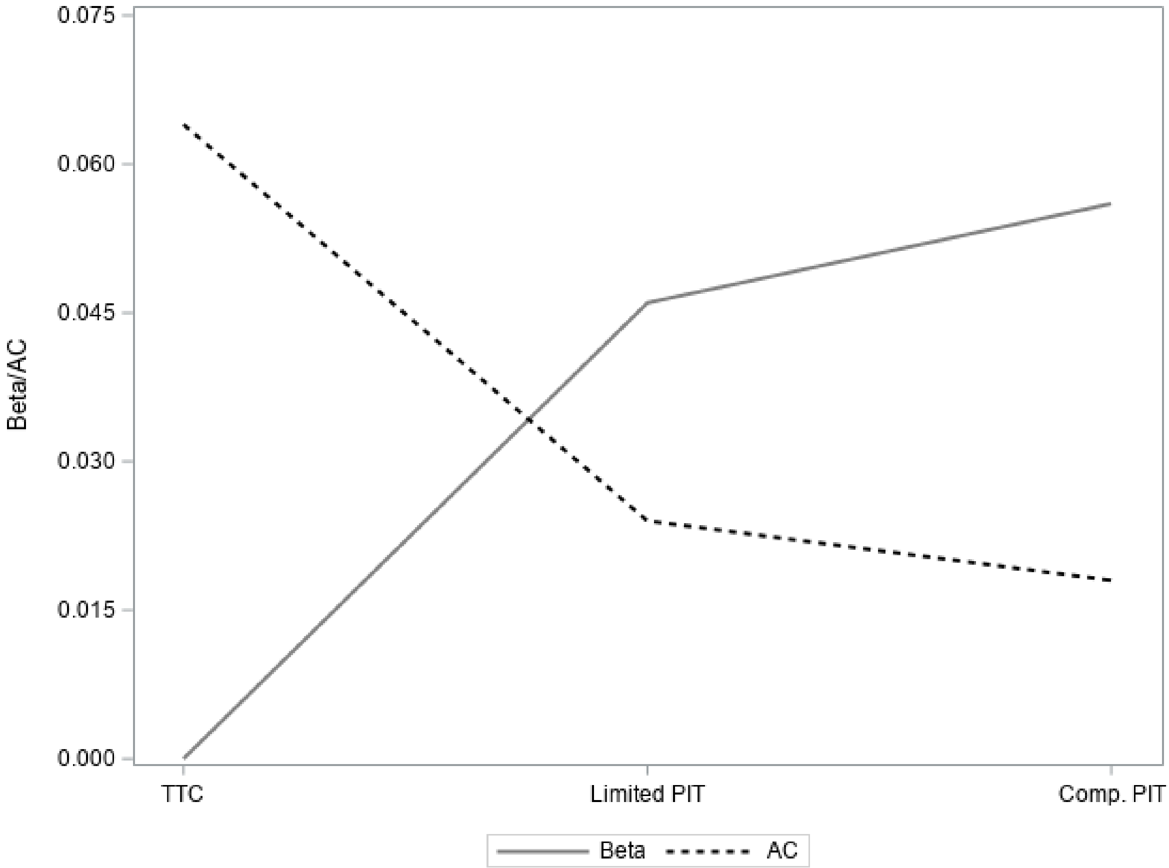


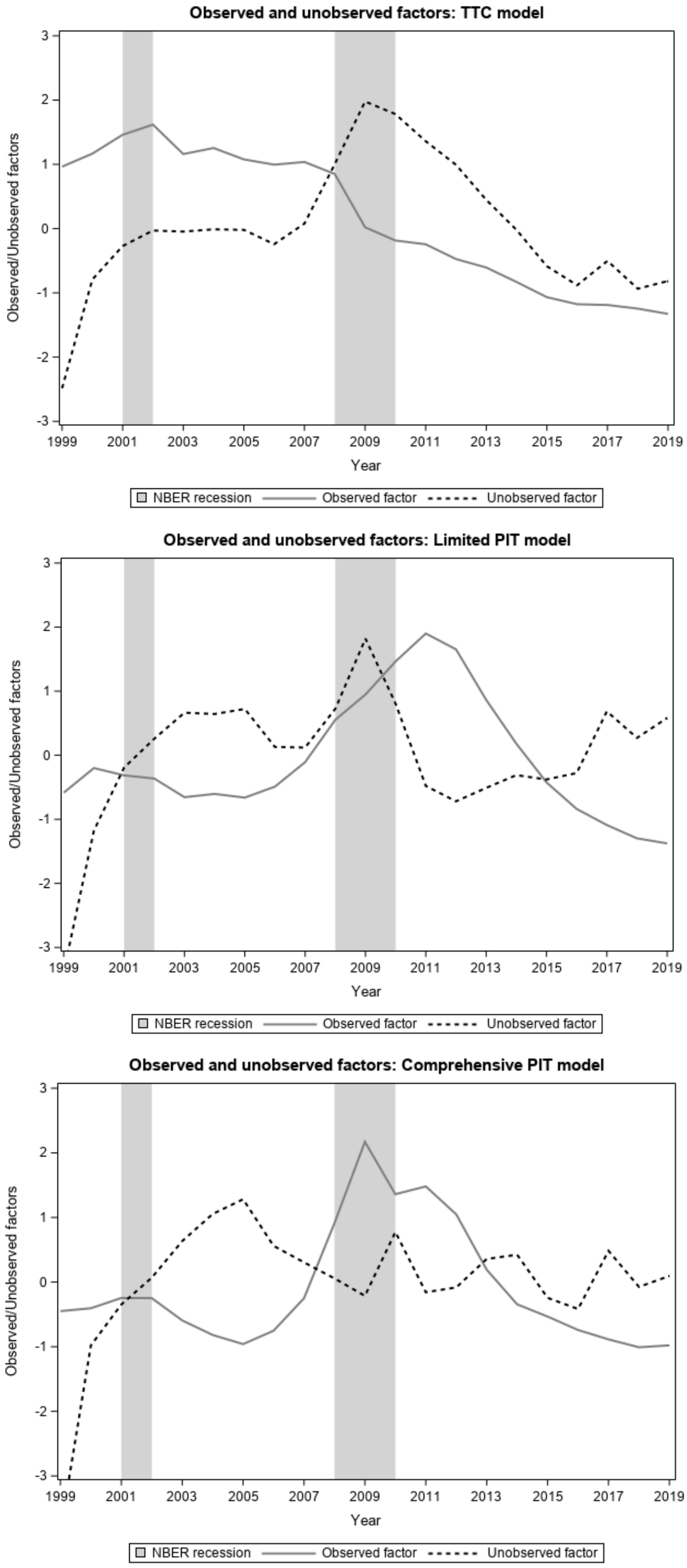
**Figure 2: Beta and AC estimates**

**Note:** This figure plots the estimates of Beta (solid line) and AC (dash line) as specified in Equation (16) based on the estimation results of three different CPD models. Each CPD model uses the standardized mean PD from the corresponding PD models, including the TTC model specified in Eq. (8), the limited PIT model specified in Eq. (9), and the comprehensive PIT model specified in Eq. (10).



# Figure 3: Observed and unobserved (frailty) systematic risk factors

**Note:** This figure plots the fluctuations of observed (solid line) and unobserved (dash line) systematic risk factors for three models over time. The observed systematic risk factor is proxied by the standardized Mean PD from the TTC model specified in Eq. (8), the limited PIT model specified in Eq. (8), and the comprehensive PIT model specified in Eq. (10). The unobserved systematic risk factor estimated from conditional PD model specified in Eq. (14). The shaded areas indicate NBER recession periods.



# APPENDIX

## Appendix A: Robustness test for regional sample

We adopt Cotter et al. (2015)'s categorization and compare our estimates with their results. Our measures would correlate perfectly to theirs if house prices were the only systematic risk driver. We find a strong association between the total systematic risk in our paper and the housing risk in Cotter et al. (2015) as the correlation is approximately 52% to 70%. The correlation is the strongest for the TTC model and the weakest for the comprehensive PIT model. As the correlation between our TTC model and their model is the highest, this could imply that the housing correlation only represents the unobserved systematic factor and could not capture the impact of the observed counterpart. That is why the correlation between our results and their results drops when we incorporate more observed factors into the model.

Looking at systematic risk components across regions, we observe that mortgages in California have substantially higher exposure to systematic risk factors than those in other regions. In the TTC model where we do not control for the observed factor, the AC estimate reaches the highest level at 13.3%. In the PIT models, the Beta estimates for California are also the highest value. This result is greatly consistent with Cotter et al. (2017), in which they find that the house price risk in CA is also the highest at 77%. Mortgages in California prove to have a much higher systematic risk than in other regions, which is likely induced by housing market risk.

For other regions, we find a similar pattern where the contribution of Beta in total systematic risk is higher than that of AC. However, this is not the case for the West South-Central region, where AC exceeds Beta in all models, indicating a more vital driving force of unobserved factors. The house price correlation in the paper of (Cotter et al., 2015) is also the smallest for this region at 22%. House prices are less likely driven by systematic factors in this region.

**Systematic risk levels across different regions (Stage 3)**

**Note:** This table presents the estimation results of Beta, AC, and total systematic risk for CA and nine regions. Pacific region includes the states AK HI OR WA; Mountain region includes AZ CO ID MT NM NV UT WY; West North Central (WNC) region includes IA KS MN MO ND NE SD; West South Central (WSC) region includes AR LA OK TX; East North Central (ENC) region includes IL IN MI OH WI; East South Central (ESC) region includes AL KY MS TN; South Atlantic region includes DC DE FL GA MD NC SC VA WV; Middle Atlantic region includes NJ NY PA and New England region includes CT MA ME NH RI VT. Beta and AC are estimated based on Eq. (18) and Eq. (19) for each region. The dependent variable is the default rate by year of each region. The independent variables are observed and unobserved systematic risk factors. Each model uses the standardized Mean PD from the corresponding PD model as the proxy of observed systematic risk factor. Unobserved factors are proxied by the set of time (year) dummies. Standard errors are in parentheses. *, **, *** indicate significance at the 10%, 5% and 1% confidence levels respectively. All results are in percentage. The last column reports the house price correlation found in Cotter et al. (2015)'s paper to compare with our estimates. The last row shows the correlation between our estimates (total systematic risk) from Cotter et al. (2015) as a benchmark.

| | Beta | | | AC | | | Total systematic risk | | | House price correlation in Cotter et al. (2015) |
|---|---|---|---|---|---|---|---|---|---|---|
| | **TTC** | **Limited PIT** | **Comp. PIT** | **TTC** | **Limited PIT** | **Comp. PIT** | **TTC** | **Limited PIT** | **Comp. PIT** | |
| CA | 0.22 | 7.582** | 11.427*** | 13.313*** | 5.416*** | 1.132*** | 13.533*** | 12.998*** | 12.559*** | 77% |
| | (0.007) | (0.029) | (0.015) | (0.033) | (0.016) | (0.004) | (0.034) | (0.028) | (0.015) | |
| Pacific | 0.004 | 4.712*** | 5.227*** | 6.166*** | 1.162*** | 1.643*** | 6.17*** | 5.874*** | 6.87*** | 44% |
| | (0.001) | (0.011) | (0.013) | (0.017) | (0.004) | (0.005) | (0.017) | (0.01) | (0.014) | |
| Mountain | 0 | 6.837*** | 8.853*** | 10.52*** | 3.22*** | 2.589*** | 10.52*** | 10.058*** | 11.442*** | 41% |
| | (0) | (0.021) | (0.021) | (0.027) | (0.01) | (0.008) | (0.027) | (0.02) | (0.022) | |
| WNC | 0.004 | 2.532** | 3.479*** | 4.134*** | 1.418*** | 1.749*** | 4.138*** | 3.949*** | 5.228*** | 27% |
| | (0.001) | (0.009) | (0.011) | (0.011) | (0.004) | (0.005) | (0.011) | (0.009) | (0.012) | |
| WSC | 0.263 | 0.348 | 1.011 | 1.177*** | 1.639*** | 5.124*** | 1.441*** | 1.987*** | 6.136*** | 22% |
| | (0.002) | (0.004) | (0.011) | (0.003) | (0.005) | (0.015) | (0.004) | (0.005) | (0.018) | |
| ENC | 0.009 | 3.29*** | 4.506*** | 5.376*** | 1.836*** | 2.179*** | 5.385*** | 5.126*** | 6.685*** | 39% |
| | (0.001) | (0.011) | (0.014) | (0.015) | (0.006) | (0.007) | (0.015) | (0.011) | (0.015) | |
| ESC | 0.175 | 1.415** | 2.27* | 2.676*** | 1.353*** | 2.996*** | 2.851*** | 2.768*** | 5.266*** | 38% |
| | (0.003) | (0.007) | (0.012) | (0.008) | (0.004) | (0.009) | (0.008) | (0.007) | (0.015) | |
| South Atlantic | 0.111 | 4.103** | 6.169*** | 7.299*** | 3.093*** | 1.81*** | 7.411*** | 7.196*** | 7.979*** | 34% |
| | (0.004) | (0.017) | (0.015) | (0.02) | (0.009) | (0.006) | (0.02) | (0.016) | (0.016) | |
| Middle Atlantic | 0.266 | 3.169*** | 3.866*** | 4.625*** | 1.139*** | 0.774*** | 4.891*** | 4.309*** | 4.64*** | 39% |
| | (0.005) | (0.009) | (0.008) | (0.013) | (0.004) | (0.002) | (0.014) | (0.009) | (0.008) | |
| New England | 0.262 | 3.952*** | 5.23*** | 6.28*** | 1.946*** | 0.953*** | 6.542*** | 5.898*** | 6.183*** | 69% |
| | (0.005) | (0.013) | (0.01) | (0.017) | (0.006) | (0.003) | (0.018) | (0.013) | (0.011) | |
| *Correlation with Cotter et al. (2015)'s results* | | | | | | | 72% | 69% | 52% | |